On the Anomaly Tilts of Factor Funds

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ABSTRACT

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, especially on the short side, and that such tilts are highly predictable. Moreover, factor-based HMFs outperform ETFs with corresponding factor tilts, which is driven by short positions and higher factor-related returns. Perversely and in contrast to HMFs, large factor tilt ETFs underperform those with contrary tilts. Overall, our results demonstrate the importance of using portfolio holdings rather than stated objectives for benchmarking factor tilts and indicate the superior factor replication ability of HMFs over ETFs.

JEL Classification: G10, G11, G14, G23

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1 Introduction

I tried telling a hedge fund manager, "You don't have alpha. Your returns can be replicated with a value-growth, momentum, currency and term carry, and short-vol strategy." He 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. ...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. For example, in Jensen (1968), the benchmark portfolio is a combination of the risk-free asset and the market index. Given the evidence of the failure of CAPM to explain the cross section of returns (e.g., Fama and French (1992)), researchers have been using the alpha from a multi-factor model to measure fund performance (e.g., Carhart (1997)). However, if investors cannot reproduce the same factor exposure themselves, then we should attribute that exposure to the value-added activity that the fund provides its investors (Berk and van Binsbergen (2015)). This is especially true in light of the recent debate on whether academic factors survive real-word implementation costs.[1] Despite the widely recognized importance of factors in asset pricing, there is little evidence to indicate that mutual funds or institutions make successful factor bets (e.g., Lewellen (2011), Patton and Weller (2019), Lettau, Ludvigson, and Manoel (2021)). In this study, we assess whether a subset of funds that are ex-ante likely to follow factor strategies tilt their portfolios towards factors, and what the performance consequences of such tilts are (both before and after implementation costs).

During the past decade, factor investing has experienced rapid growth of approximately 11% per annum, reaching an estimated \$1.9 trillion in assets under management (AUM) by 2017 (Wigglesworth (2018)). Several asset managers (e.g., AQR, Dimensional, Invesco, and Robeco)

[1] E.g., Novy-Marx and Velikov (2016), Frazzini, Israel and Moskowitz (2018), Briere, Lehalle, Nefedova and Amine (2019), and Chen and Velikov (2021).

have become very successful by adopting a factor-based investment approach. Although some of these products are only available via hedge funds or separate accounts, investors can also participate in factor investing via so-called Hedged Mutual Funds (HMFs) and smart-beta Exchange-Traded Funds (ETFs). 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 267 U.S. equity-focused HMFs and 287 smart-beta ETFs, we assess whether they tilt their portfolios to exploit factors.[3] Furthermore, we examine the performance implications of such tilts, by comparing HMFs against smart-beta ETFs. We contrast the two types of investment vehicles, because index funds/ETFs represent a more passive (and significantly cheaper) way for investing in the factors and are widely used for benchmarking mutual fund performance both by academics (e.g., Berk and van Binsbergen (2015), Chakraborty, Kumar, Mulhefer and Sastry (2020)) and by investors (e.g., Sensoy (2009), Evans and Sun (2021)).

We focus on four factors that are widely used both in academia and by 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 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. For HMFs, the total long-short factor tilt is a weighted average of the long- and short-side factor tilts, with weights given by the percentage of AUM invested.[4] This method is robust to

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[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 113 ETFs in traditional styles (e.g., standard value, and growth), as well as a newer generation of 66 single-factor ETFs (value, momentum, quality, and low-risk) and 108 active/multi-factor ETFs.

[4] E.g., a 130/30 value fund might have a positive value tilt on the long side (e.g., +1 decile above the market), and vice-versa for growth stocks on the short side (-1 decile), resulting in a total value tilt $1.3 \times 1 - 0.3 \times -1 = 1.6$.

outliers, easy to interpret and is closely related to how factor strategies are typically implemented. Characteristics can also be computed from a single holdings snapshot, which is useful for capturing up-to-date factor exposures.

In our first set of results, we show that HMFs and ETFs tilt significantly toward the four anomalies. 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. The total factor tilt is appropriate for classifying factor funds as long as the individual tilts are not highly correlated, which they are not.[5]

To better assess the economic significance, we evaluate the persistence in total factor tilts. We start by dividing funds into four groups: large factor tilt (comparable to academic factor benchmarks), moderate (halfway towards the factor benchmark), marginal, and contrary. The proportion of funds with large factor tilts (large + moderate) is substantial, at about 31% (52%) for HMFs, 39% (67%) for active/multi-factor ETFs and 22% (52%) for single-factor ETFs. By contrast, funds that bet at least moderately against factors (contrary tilts) are less than 20% of the overall sample. Importantly, these classifications are highly persistent. Conditional on having a large factor tilt in the current quarter, HMFs (active/multi-factor ETFs) [single-factor ETFs] have a total factor tilt that is as much as 3.5 (2.4) [1.9] deciles above the market in the next quarter. Despite their high turnover (e.g., 244% for HMFs), there is very little decay in the total factor exposures for horizons up to at least a year. Investors who are able to evaluate factor tilts (e.g., by

[5] Among NYSE stocks, the largest (absolute) correlation is between value and asset growth (0.11). Nevertheless, we account for this when comparing factor tilts relative to appropriate academic factor benchmarks. This is a more serious problem when considering a broader set of anomalies (e.g., Stambaugh, Yu, and Yuan (2012)).

using the factor profile in Morningstar) can therefore pick factor funds based on ex-ante information.

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 relative to the market, especially on the short side. Since asset pricing anomalies are more profitable for small-cap stocks (e.g., Hou, Xue, and Zhang (2020)) and on the short side (e.g., Stambaugh et al. (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.[6] This is especially important since Patton and Weller (2019) show that factor risk premia estimated from (long-only) mutual fund returns are low compared to those estimated for hypothetical test portfolios.

Importantly, we show that multiple factors are relevant for factor-based funds. Specifically, we find that the vast majority of large factor tilt funds target multiple factors: 93% of HMFs, 76% of active/multi-factor ETFs and, surprisingly, about two-thirds of single-factor labelled ETFs (based on stated investment objectives). Labels are therefore misleading about the factors that a fund is actually exposed to. Moreover, we demonstrate the importance of properly benchmarking the factor tilts of these funds: large tilt HMFs and ETFs with a multi-factor holdings-based focus have comparable factor tilts to those of an academic multi-factor benchmark.[7]

[6] These results complement those by Gao and Wang (2021), who show that the HMFs in aggregate trade on several anomalies on the short side, and that such trades predict future stock returns. Our focus is different, however, because we examine the *level* of factor tilts at the fund level rather than *changes* in factor tilts for the aggregate short-side HMF portfolio. From an investor's perspective, a relevant and still unanswered question is whether factor-based HMFs can be selected ex-ante, and what the performance implications of their factor tilts are, relative to cheaper ETFs.
[7] This benchmark assigns equal weight to the four single-factor benchmarks; each single-factor benchmark is a value-weighted portfolio that targets the top tercile on a particular characteristic.

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 and to what extent these funds replicate the performance of the underlying factors. To answer these questions, we focus our analysis on cross-sectional differences in performance between HMFs and ETFs, or by the degree of the factor tilt within the same fund type, over the 2010-2019 time period. 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. This is not only about their ability to short sell securities, but also about the fact that HMFs are not constrained to mechanically follow a pre-determined index or 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 between HMFs and ETFs. Multi-factor HMFs with large factor tilts outperform corresponding ETFs by up to 2.17% per year when measured using CAPM alphas. A fund can deliver positive CAPM alphas either by successfully replicating factor strategies (with a significant risk premium), by factor timing (e.g., Ehsani and Linnainmaa (2021)), and/or by engaging in security selection. To identify the contribution of short positions to the replication of factor strategies, we remove them from the holdings-based returns and find that the alphas are substantially lower. To better isolate stock picking ability, we consider Fama-French 6-factor alphas (Fama and French (2018)) and DGTW characteristic-adjusted returns. In the former case, the performance difference becomes insignificant, while in the latter case it drops by half but remains highly significant. We also find some evidence of positive factor timing ability among

HMFs with large factor tilts. Overall, these results suggest that the outperformance of HMFs with large tilts stems primarily from short positions and general factor replication/timing ability.

Despite doubts raised by recent studies (e.g., Patton and Weller (2019)) about the factor replication ability of fund managers net of implementation costs, the outperformance of HMFs with large factor tilts remains largely unchanged when using actual (gross) returns, and after dropping derivative users from the sample. 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 factor-replication ability of smart-beta ETFs. Whereas HMFs with large factor tilts outperform HMF with contrary tilts by as much as 2.72% per year net of all costs and fees, ETFs with large factor tilts tend to underperform ETFs with contrary tilts, whether using CAPM or FF6 alphas. Overall, these results are robust to variety of methods, including regressions, calendar-time portfolios and benchmarking HMFs to similar ETFs in the factor space (in the spirit of Hoberg, Kumar and Prabhala (2018)).

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, Ince, and Kadlac (2016) actually report that institutions in aggregate trade contrary to anomalies in the period prior to the realization of anomaly returns. However, there is evidence that institutions trade in the right direction if one focuses on sophisticated investors, such as hedge funds (e.g., Cui, Kolokolova, and Wang (2020)), and on the period after publication (Calluzzo, Moneta, and Topaloglu (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 economically meaningful factor tilts. Our results differ from theirs for several reasons. 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 Fama-French factor benchmark that corresponds with the fund's stated objective, which we show is inaccurate. By contrast, our evidence suggests that most HMFs and smart-beta ETFs have a multi-factor focus, and that using a multi-factor benchmark dramatically increases their factor tilts.

Earlier studies on HMFs focus 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 financial crisis period. Gao and Wang (2021) 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 factor replication ability of HMFs at the fund level, and we are the first to compare HMFs against smart-beta ETFs.

The literature on smart-beta ETFs is more recent and offers some criticisms. Huang, Song and Xian (2021) 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. By contrast, we show that the vast majority of funds actually target multiple factors (in contrast to their stated objectives) and they often have large factor tilts, while those that target a single factor often have offsetting factor exposures that result in small total tilts.

2 Data and Sample Selection

Our sample consists of U.S.-based Hedged Mutual Funds (HMFs), or alternative strategy funds, and smart-beta Exchange-Traded Funds (ETFs). We identify these funds using Morningstar Direct, which contains both live and dead funds and is free of survivorship bias. Additional details on the sample selection are provided in Sections 2.1 and 2.2. The sample period for HMFs starts in January 2006, which coincides with the introduction of the first alternative strategy category in Morningstar Direct; for ETFs we start in January 2010 since there are few factor-based ETFs prior to this time. The sample period for both set of funds ends in December 2019.

We collect data on fund returns, expense ratios, and assets under management (AUM) from the CRSP Survivor-Bias-Free U.S. Mutual Fund database (henceforth CRSP MFDB).[8] 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.

[8] Following the procedures in Berk and van Binsbergen (2015) and Pastor, Stambaugh, and Taylor (2015), we reconcile differences in mutual fund returns and AUM between CRSP MFDB and Morningstar Direct. Additional details are provided in Sections IA-1 and IA-2 of the Internet Appendix. In addition, we remove a handful of unusually large weight changes (+/-100%) in equity positions by cross-checking with the historical annual/semi-annual N-Q holding reports filed with the SEC.

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 stock). Although we only include only 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 (2021) for additional details). Funds are required to have a minimum of two years of holdings data (e.g., as in Jian, 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 start by selecting the following Morningstar Categories that are under the alternative strategies header: i) long-short equity, ii) leveraged net long, iii) bear market, iv) market neutral, v) multi-alternative, and vi) options-based.[10] Funds in i) and ii) use both long and short positions while maintaining a net long exposure (e.g., 130%/-30%); bear market funds maintain a

[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 February 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.

[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.

net short position on average; and market-neutral funds typically have more equal long and short equity exposures. Funds in the remaining two, multi-alternative and option-based, may also invest in fixed income (in the former case), or in derivatives (in both cases), while maintaining a substantial equity allocation as well. Our initial selection therefore keeps funds in any of the six categories, but we filter out non-equity funds (including derivative users) based on several dynamic screens (discussed next). We further 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 over some period of time, 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 the latter to account for the increased flexibility of HMF strategies. To account for a total gross leverage in excess of 100% (the full sample average is 116%), we require that gross equity leverage and the proportion of risky assets invested in equities (gross equity leverage / total gross leverage) are both at least 50% at *t*-1.[11]

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

[11] This filter removes funds that primarily use non-equities as well as funds that use derivatives (whether equities or non-equities). The latter is true because derivatives are not included in our leverage calculations due to inconsistent reporting of their magnitude (market vs. nominal values) in Morningstar.

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 (2021a)). Morningstar also has a 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 (e.g., multi-factor funds may be called active beta, strategic factors, or factor tilt). Following Ben-David, Franzoni, Kim, and Moussawi (2021), we use Morningstar's Strategic Beta category variable to identify smart-beta ETFs. Our goal at this stage is simply to narrow down the universe to ETFs that actually target factors. In Section 3.3 we show the limitations of Morningstar categories, and by extension stated investment objectives (e.g., used in Lettau et al. (2020)), in benchmarking factor exposures.

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).

We make a few changes to the Strategic Beta categories to better align them with the factors considered in this study. First, we create a separate category for factor-based value strategies by manually going through the strategy descriptions of all value ETFs. The reason is that standard value indices from major index provides (such as MSCI, S&P, Russell, or CRSP) rank stocks not just on value characteristics, but also on earnings growth characteristics. 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). These ETFs have substantially greater value tilts compared to standard value funds (shown later). Second, although two-thirds of dividend-screened/weighted ETFs are similar to standard value funds in terms of their overall factor tilts, the remaining one-third of funds target stocks with consistently high dividend growth rates. These funds, identified by the Morningstar Category variable being equal to blend or growth, are reclassified as Quality since they have factor tilts that are very similar to quality ETFs. Third, we re-label “risk oriented” as “low risk” and remove a handful of high beta/high risk funds, as well as funds that seek to manage risk by tactically switching between equities and treasuries/cash.

2.3 Descriptive Statistics

Summary statistics on the number of funds, fund size (AUM), expense ratios, 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 267 HMFs and 287 smart-beta ETFs. The category with the most HMFs is long-short equity (115), followed by multi-alternative (49), market neutral (45), options-based (37), leveraged net long (17). As for ETFs, the largest categories are multi-factor (65) and actively managed (43), followed by traditional style categories—dividend yielding (42), growth (30), and standard value (27). The newer generation of single-factor ETFs includes quality (29), 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 84% of their capital to long equity positions and 52% to short equity positions. While multi-alternative funds have the lowest gross equity leverage on average, it is still meaningful at 62% and 19% on the long- and short-side respectively. Funds in most categories hold negligible amounts (< 5%) in fixed income securities, except for multi-alternative funds (18%). Options-based funds hold large equity positions on the long-side (90% on average), but short positions are marginal (2%). 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 $2 to 5 billion, compared to single-factor categories (e.g., factor-value, momentum) that are closer to $0.5 billion. Multi-factor and actively managed ETFs, many of which have a multi-factor tilt as we will see later, are substantially smaller at $290 and $90 million in AUM on average, respectively. These numbers are not all that different for HMFs, where the average size is between $120 and $900 million. Expense ratios, on the other hand, are less than a third for ETFs (generally < 0.5%) compared to HMFs (1.2-1.5% on average), indicating a distinct cost advantage for the former. These patterns are consistent with the Easley, Michayluk, O'Hara and Putnin (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 (Book-to-Market, Earnings-to-Price, Sales-to-Price and Cash Flow-to-Price; *VAL*), ii) momentum based on *t*-2 to *t*-12 past returns (*MOM*), iii) (conservative) asset growth (total asset growth and net equity issuance; *CAG*), and iv) operating profitability (*PROF*). We consider multiple value metrics because that is standard practice for benchmarks used by both mutual funds and ETFs (see e.g., Lettau et al. (2021)). Nevertheless, our results remain similar when using the industry-adjusted B/M ratio (e.g., Daniel et al. (1997)), or the intangibles-adjusted B/M ratio by Eisfeldt, Kim, and Papanikolaou (2021).[12]

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 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 $C_{j,t} = d, d \in \{1,2,3 \dots 10\}$. These scores are aggregated to the fund-level by taking the portfolio-weighted average of the stocks held by the fund:

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

[12] There is a recent debate on the "death" of the value strategy due to its extremely poor performance in the past two decades. Arnott, Harvey, Kalesnik, and Linnainmaa (2021) argue that the B/M ratio is an outdated metric that is no longer useful for capturing the value premium. Alternative definitions of value, especially the intangibles-adjusted B/M, but also the industry-adjusted B/M, have performed significantly better. The latter is justified by prior research (see e.g., Asness, Porter, and Stevens (2000), Cohen, Polk, and Vuolteenaho (2003), Golubov and Konstantinidi (2019), and Eisfeldt, Kim, and Papanikolaou (2021)). Appendix 1 provides additional details on the factor definitions.

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. When computing the value tilt, for example, we take the average characteristic score across the four price multiples (B/M, E/P, S/P, and CF/P). Third, decile scores are closely related to how factor strategies are typically implemented.

As a benchmark for the fund-level characteristic scores, we start with the market portfolio. This 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 therefore expected to generate outperformance relative to the market on average. Hence, we reverse the order for asset growth, so that higher values indicate conservative (lower) asset growth (and higher expected returns). 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)).

[13] For factor-based ETFs we use the Morningstar 3-by-3 size-valuation box to determine whether a fund has a small-cap orientation. For HMFs we use instead the average of the long- and short-side size characteristic score over the prior two years. Small-cap ETFs have an average size decile score of 5.75. We use the same cut-off for HMFs. Results are similar if we instead use Vanguard's Total Stock market ETF (ticker: VTI) which holds > 4,000 stocks.

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 $\left(w_{i,t}^{+}\right)$ or short $\left(w_{i,t}^{-}\right)$ positions:

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

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. In the subsequent analysis, we also consider hypothetical factor benchmarks that are typically used in the asset pricing literature.

3.1 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. Standard errors are clustered by fund throughout this study. In contrast to Lewellen (2011) who finds that the aggregate institutional investor portfolio is not tilted towards anomalies and Edelen et al. (2016) who find that institutions on average trade *against* anomalies, our results suggest that HMFs tilt significantly towards value (by 0.40 deciles), momentum (0.26 deciles), conservative asset growth (0.27 deciles), and profitability (0.11 deciles). The individual tilts may at first glance appear economically small, but this is to be 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 1.04 deciles away from the market portfolio on average when using all four factors. As we will show in more detail later, a one decile total factor tilt is roughly halfway towards academic factor benchmarks (top tercile of stocks, value-weighted). Furthermore, these averages hide a substantial degree of cross-sectional variation with a meaningful subset of funds betting as strongly as academic factors do, which we will explore in the next section. Our 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.

Moreover, the factor tilts by HMFs are on average substantially greater on the short side (2.0 deciles below the market), compared to the long side (0.38 deciles above the market). 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 (2014)), 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 (2021), 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 *fund level* rather than changes in factor tilts for the aggregate short-side HMF stock portfolio.[14] From an investor's perspective, a relevant question is whether HMF portfolios provide meaningful exposure to anomalies, how persistent these tilts are, and whether they can obtain similar exposure through cheaper ETFs. This question is better addressed by

[14] In Table 2, the authors 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.

focusing on the complete long-short portfolio of HMFs and by examining the level of exposure rather than the change.

[Table 2]

The total factor tilts for actively managed and multi-factor ETFs are very similar to those of HMFs with meaningful tilts on multiple factors (around 1 decile above the market in total, see Panel B). Among the single-factor labelled ETFs, we see especially large value tilts among factor value ETFs (+2.3 deciles, see Panel B), and momentum tilts for momentum ETFs (+1.4 deciles). Although quality ETFs also load meaningfully on the profitability factor (+1.0 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 quality ETFs (+0.6 deciles).[15]

A pervasive feature of many smart-beta ETFs that has previously not been documented are the offsetting tilts to other factors. Standard value ETFs, for example, have significantly positive tilts on value (+1.1 deciles) and asset growth (+0.47 deciles), but negative tilts on momentum (-0.47 deciles) and profitability (-0.45 deciles). These offsetting tilts arise because such funds target stocks with both high value and low earnings growth rates. As a result, the total factor tilts for standard value and growth ETFs, as well as momentum funds, are substantially lower than for HMFs. To establish a proper basis for comparison and address the possibility that the offsetting tilts are simply the result of a negative correlation between two factors, we analyze to what extent academic factor benchmarks—targeting the top tercile of stocks on a particular characteristic—have offsetting tilts (results unreported for conciseness). Value and momentum benchmark

[15] We do not focus on the low-risk anomaly because it is correlated with the profitability and asset growth anomalies (Novy-Marx and Velikov (2021)). We nevertheless 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. We include low risk ETFs in the analysis of performance. These results are not material different if we drop them.

portfolios have relatively small offsetting tilts. For example, the academic momentum benchmark has a momentum tilt of 1.9 and a total factor tilt of 1.6. Asset growth and profitability benchmarks do not have offsetting tilts at all. In general, the offsetting tilts for smart-beta ETFs are far worse than for academic factor benchmarks, which is new to the literature.

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 funds with large factor tilts ex-ante? It is not at all obvious in light of the high reported turnover of not only HMFs (244% per year), but also actively managed ETFs (162%) 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 *contrary* factor tilt is a portfolio where the total factor tilt is meaningfully negative (below -0.5 deciles). A *marginal* factor tilt corresponds to an insignificant factor tilt (-0.5 < total factor tilt < 0. 5 deciles). A *moderate* factor tilt is a portfolio with 0.5 ≤ total factor tilt < 1.5 deciles. A *large* factor tilt is a portfolio with a total factor tilt ≥ 1.5.

The fixed cut-off for *large* is similar to what we observe for academic factor benchmarks, which target stocks in the top tercile on a particular characteristic, similar to Fama-French and others. Specifically, academic factors have total factor tilt of around 2.2 deciles above the market. This is true both for single-factor benchmarks (e.g., top tercile on 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. The chosen cut-off for *large* factor tilt (1.5) is somewhat below 2.2, because factor funds may target other factors besides the four that we consider here. For example, a multi-factor benchmark that equally weights five single-factor benchmarks (*VAL*, *MOM*, *CAG*, *PROF* plus low vol) would have a total four- (five-) factor tilt of 1.6 (2.1) deciles above the market.

The results in Table 3 provide strong evidence of persistence in factor tilt classifications. In particular, HMFs with large factor tilts in the previous quarter have, on average, a total factor tilt of 3.5 deciles above the market in the next quarter. Both the long- and the short-side contribute meaningfully, although the magnitude on the short side remains more than twice as large in absolute value (1.8 vs. -3.9 deciles). Nearly identical results are obtained when lagging the factor tilt classification by four quarters instead of one.[16] 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 2.4 (1.9) deciles above the market at q.

[Table 3]

Almost as important as the magnitude of factor tilts is the proportion of funds with large factor tilts and, in the case of HMFs, how much leverage they use. Table 4 shows that around 31% of the sample of HMFs have large factor tilts and the majority of HMFs (52%) have moderate or large factor tilts. If we separately examine the long- and short-side sub-portfolios, we can see that about 23% and 53% of funds have large factor tilts. Importantly, funds with large factor tilts also have high gross equity leverage, at 100% and 46% for long and short positions respectively, compared to 82% and 18% for funds with moderate tilts.[17] For ETFs, the proportion of funds with

[16] The magnitude (statistical significance) of total factor tilts falls by almost a third (half) if we instead sort funds on the total short-side factor tilt. This result speaks to the importance of using the complete (leveraged long and short) portfolio rather than focusing only on the short side (e.g., as in Gao and Wang (2021)).
[17] 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.

large factor tilts is very high for active/multi-factor ETFs at 39%, but lower for single-factor labelled ETFs at 22%. A smaller but still sizeable fraction of funds have contrary factor tilts—about 18% of HMFs, 20% of single-factor labelled ETFs, and 13% of active/multi-factor ETFs.

[Table 4]

We also compare the persistence of individual vs. total factor tilts using simple autoregressive models. 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-4 show that for multi-factor HMFs with large factor tilts, the total factor tilt is far more persistent than any individual tilt, while the opposite is true for their ETF counterparts. 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 tilts.

Overall, the results in this section confirm that factor tilts are highly persistent for both HMFs and ETFs, and that a significant subset of funds have large factor tilts. This result stands in contrast to Lettau et al. (2021), who argue that the factor tilts of mutual funds, ETFs, and 13-F hedge fund companies are concentrated around the market average with very little variation across funds (<1% have meaningful factor tilts). Our results are explained by three major differences between our work and theirs. First, we focus on a subset of funds that ex-ante are more likely to trade on factor strategies. Our perspective is therefore more about the marginal investor in factor strategies rather than the average investor. Second, 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. Third, we have so far measured factor tilts vis-à-vis the market portfolio. Given that institutions as a whole closely mimic the market portfolio (Lewellen (2011)), we argue that the market portfolio is an important benchmark on its own. By contrast, Lettau et al. (2021) evaluate factor tilts relative to the Fama-French factor benchmark that corresponds with the fund's stated investment objective, as inferred from the fund's name. As we will show in the next section, stated objectives are often misleading and it is more accurate to use portfolio holdings to determine an appropriate factor benchmark.

3.3 Choosing an Appropriate Factor Benchmark

Evaluating factor tilts relative to a factor benchmark (rather than the market portfolio as done in Section 3.1) is useful for gauging how close actual portfolios are to academic factor benchmarks considered in existing literature. In the case of value funds, Lettau et al. (2020) compare a fund's value tilt relative to the value tilt of the long-leg of the HML factor. We argue that such single-factor benchmarks are misleading for HMFs and ETFs, because most factor-based funds 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. This cut-off is actually lower than what academic single-factor benchmarks have (typically above 80%). Based on this definition, we find that the vast majority, or 93% (29.2 divided by 31.4; see Table 4), of HMFs with a large factor tilt have a multi-factor focus compared with 50% for HMFs with a moderate tilt. A similar pattern is observed for active/multi-factor ETFs. Surprisingly, we find that around two-thirds of single-factor labelled ETFs with a large factor tilt actually have a multi-factor holdings-based designation. Single-factor benchmarks are therefore appropriate only for a relatively small subset ETFs. For the rest, including most HMFs, we need to consider multi-factor benchmarks.

In Table 5, Panel A, we present results for the factor tilts of ETFs relative to single-factor benchmarks, which correspond to hypothetical portfolios that take positions in the top tercile of stocks on a particular characteristic. We compute fund-level factor tilts by subtracting from the fund-level characteristic score (e.g., value) the value-weighted characteristic score of the corresponding single-factor benchmark (e.g., top tercile of value stocks). For the full sample of ETFs, factor tilts are significantly below the corresponding single-factor benchmark. This result is consistent with Lettau et al. (2021), who argue that virtually no ETFs or mutual funds have meaningful factor tilts. However, if we instead focus on the subset of funds with large factor tilts and a single-factor holdings-based designation, we find that Factor Value, Momentum and Quality ETFs are relatively close to their single-factor benchmarks at -0.35 deciles, +0.32 deciles and -0.42 deciles respectively. These results suggest that while the proportion of funds with a single-factor holdings-based designation is fairly low—between 7-10% of the overall ETF sample, although their aggregate AUM remains substantial compared to HMFs, see Table 1—such funds do in fact have comparable factor tilts to those considered in the academic literature.[18]

[Table 5]

Ultimately, our focus should be on multi-factor benchmarks, since the vast majority of funds have exposures to multiple factors. There are arguably many different ways to construct a multi-factor benchmark. We seek a benchmark with balanced tilts on all four factors. Hence, we assign equal weight to the four single-factor benchmark portfolios examined earlier (with stocks

[18] In contrast to Lettau et al. (2020) who equally weight Large Value and Small Value, we compare the value tilt of a large- (small-) cap fund only against LV (SV). It is not appropriate to benchmark large-cap funds against SV since mutual funds are constrained by their investment mandate and tracking error from investing too much outside of their benchmark (e.g., He and Xiong (2013)). In addition, regulatory constraints rules limit mutual funds from investing more than 15% in illiquid assets (www.sec.gov/divisions/investment/guidance/secg-liquidity.htm).

within each of the four being value-weighted). This is sometimes referred to as a mix of stand-alone factor sleeves, or a top-down approach, in the industry.[19]

We present these results in Table 5, Panel B, separately for HMFs and ETFs. In this case, we report the pooled fund-quarter average total factor tilt, 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). While the full sample results indicate that the average HMF is far from its multi-factor benchmark, we do observe some intriguing cross-sectional differences that are entirely new to the literature. Namely, funds with a large factor tilt and a multi-factor focus, based on our holdings analysis, have a total factor tilt that is *insignificantly* different from the multi-factor benchmark in the subsequent quarter. We also take a closer look at the long- and the short-side of these funds' portfolios. While the long-side factor tilt is marginally below the multi-factor benchmark (by 0.3 deciles), the short side is actually tilted more towards anomalies by a significant 1.0 deciles. 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 with large factor tilts and a multi-factor designation. 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) can be misleading.

[19] We confirm in unreported tests that HMFs with large factor tilts on average have roughly equal tilts on all four factors. We also consider a bottom-up approach, where each stock receives a weight that is proportional to the value-weight times the proportion of factor portfolios that a stock belongs to. For example, value weight × 1 if the stock is in all four factor portfolios simultaneously and value weight × 0.5 if a stock is in two out of four factor portfolios. The drawback with this method is that the factor tilts are not as balanced as for the top-down approach.

When we use the correct benchmarks, there are meaningful subsets of ETFs and HMFs that provide factor exposure similar to the academic factors.

3.4 Robustness: Factor Loadings vs. Characteristics

In comparison to factor loadings (i.e., the betas from regressions of fund returns on factor returns), 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 3.4. 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 et al. (2014), Kamara, Korajczyk, Lou, and Sadka (2016), Bandi, Chaudhuri, Lo, and Tamoni (2020)). Equally weighting the large and small-cap portfolios used to construct factor returns may also be inappropriate (Grinblatt and Saxena (2018)), especially when the actual investment universe excludes many of the smaller stocks included in the factor portfolios.

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-5, 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 a major subset of 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 and whether or to what extent these funds successfully replicate the performance of the underlying factors.

Each fund structure has its pros and cons. On the one hand, ETFs provide factor exposure at low prices, 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 (2015), Christoffersen and Simutin (2017)), which is contrary to the low-risk anomaly. On the other hand, HMFs are more flexible 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 practitioners (e.g., Arnott and Kalesnik (2017); Malkiel (2014)) and academics (Huang, Song, and Xian (2021)) about the factor replication ability of smart-beta ETFs. 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 i) the positive externality that arises when groups of investors reduce each other's price impact due to trading diversification across factor strategies (DeMiguel, Martin-Utrera, and Uppal (2019)), or ii) the higher returns on anomaly strategies in a short window surrounding information events (Bowles, Reed, Ringgenberg, and Thornock (2020)), in contrast to passive ETFs which 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 shift our focus to cross-sectional differences in performance between ETFs and HMFs over the common 2010-2019 time period.

We focus initially on hypothetical holdings-based measures of performance, but later we also consider the fund's actual performance to shed light on the importance (or lack thereof) of implementation costs, within-quarterly trades, and fixed income/derivative positions. A fund can deliver positive market-adjusted returns by successfully replicating factor strategies (with a significant risk premium), by factor timing (e.g., Ehsani and Linnainmaa (2021)), or by engaging in security selection. We start with CAPM alphas, which capture both security selection and factor-related returns. To control for the performance of factor tilts and isolate the security selection, 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).[20] We also consider DGTW characteristic-adjusted returns and characteristic timing (Daniel et al. (1997)), which do not require the estimation of the betas.

[20] 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. 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, we also report results using the more traditional approach of using returns over a rolling 36-month window to estimate factor loadings. Although the results continue to hold, this approach is inappropriate because of the time-variation in HMFs' factor exposures (see Section 3.4 and 3.5).

4.1 Regression Results

We estimate pooled OLS regressions of fund performance on lagged factor tilt dummies (contrary, moderate, and large) interacted with a HMF dummy, separately for the full sample and for multi-factor funds only. The results in Table 6 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 short positions. 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), or between large and contrary tilt funds of the same fund type.[21]

[Table 6]

Panel A provides the results for holdings-based CAPM alphas in columns (1), (2), (5), and (6). We find that HMFs with large tilts outperform corresponding ETFs by a highly significant +17-18 bps per month (see last coefficient of column (1) for the full sample and (2) for multi-factor funds only). We also observe a substantial decline in the multi-factor HMF-ETF performance difference to an insignificant 3 bps per month (among funds with large tilts) when using only the long-side portfolios of HMFs (column (5) and (6)). This decline is economically even more meaningful if we consider the fact that the weight invested in short positions is only

[21] The omitted (benchmark) group includes HMFs and ETFs with marginal factor tilts. However, the relative performance differences that we focus on (e.g., large tilt HMF vs. large tilt ETF) are unaffected by this choice. 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).

about half of that for long positions (see Table 4). Hence, short positions largely explain the outperformance of factor-based HMFs perform over their ETF counterparts.[22]

Aside from short positions, the differences in CAPM alphas may be attributed to factor tilting, timing, and/or stock picking. 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 HMFs vs. ETFs with large factor tilts disappears, regardless of specification, when using FF6 alphas. Estimation issues with the factor loadings (see Section 3.5) may play a part, however. As an alternative measure that does not require the estimation of factor loadings, we consider DGTW characteristic-adjusted returns in Panel B. In this case, we observe a smaller but still highly significant performance differential between HMFs and ETFs with large factor tilts of around 5.6 bps per month (full sample) and 8.5 bps per month (multi-factor funds only), which become insignificant for long-only portfolios (implying again that short positions matter). Moreover, DGTW characteristic-timing performance is also significantly positive, especially for multi-factor funds, at approximately 3.7 bps per month (column (4)). In this case, long positions also contribute meaningfully to the timing performance (column (8)). Part of this outperformance may, however, stem from positive returns on the Investment and Profitability factors, which are absent from the DGTW benchmark.

Our results so far are consistent with the notion that HMFs, although they do not exhibit superior stock picking ability, they have superior factor replication and timing ability, compared

[22] To rule out the alternative explanation that the outperformance of HMFs with large factor tilts (i.e., ≥1.5 deciles) relative to similar ETFs (≥1.5) is due to greater factor tilting by the former, we re-estimate the regression by replacing the factor tilt dummies by its continuous version (i.e., the sum of factor tilts), and the interaction with a HMF dummy. For a given level of total factor tilt, the impact on performance is indeed significantly greater for HMFs than ETFs. These results are unreported for conciseness.

to ETFs.[23] As further evidence of the factor replication ability, we compare funds of the same type with large vs. contrary tilts. This difference remains a highly significant +22 bps per month for multi-factor HMFs when measured using CAPM alphas (see Table 6 Panel A). By contrast, the performance difference for ETFs is actually negative with point estimates of -11 bps for CAPM alphas (insignificant) and -15 bps for DGTW characteristic-adjusted returns (significant at the 5% level). The inflexibility of factor-based ETFs in replicating the underlying factors and the underweighting of smaller-capitalization stocks (see Table IA-1 and IA-8), compared to HMFs, is the likely culprit in the poor performance of these funds.

5 The Impact of Derivatives, Unobserved Actions, and Fees

So far we have used quarterly equity holdings to assess factor tilts and measure fund performance. Since HMFs hold negligible amounts in (non-cash) fixed income securities (< 5%, see Table 1), we should be able to infer the overall factor tilt of a HMF by only using its equity portfolio. Nevertheless, a potential concern is that we ignore their derivative positions. While the proportion of derivative users is substantially lower among funds with large factor tilts (at 33%), compared to other funds (64%), it is clearly not zero. If a fund uses derivatives to alter the market risk exposure, or to gain exposure to other factors, then drawing conclusions based only on the equity portfolio may be inaccurate. We assess the impact of derivatives on factor exposures in Section 5.1. 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

[23] In the Internet Appendix, Table IA-7, we also consider a multi-factor extension of the timing/tilting performance measures of Kacperczyk et al. (2014). These results suggest that factor-based HMFs have significantly higher factor-related tilting performance, compared to ETFs, of approximately 8-9 bps per month, respectively.

reflected in the reported holdings (Kacperczyk, Sialm, and Zheng (2008)). We evaluate the impact of these in Section 5.2.

5.1 Derivatives Use

To assess the impact of derivatives on factor exposures, we evaluate the *difference* between actual (obtained from net returns) and holdings-based factor loadings. Derivatives may be used to alter the market risk exposure, which is important for the analysis on fund performance and factor replication ability. Indeed, we find that all sub-samples, except large tilt multi-factor funds, have significantly *lower* actual than holdings-based CAPM betas by about 0.12 (see Table 7, column (1)). These differences fall by more than half if we drop funds that use derivatives (column (2)), or by about half if we instead drop funds that belong to the options-based and/or multi-alternative categories (columns (3) and (4)). Derivatives are therefore likely to be used for hedging market risk (e.g., via protective puts), which would explain the lower CAPM betas of net returns. As for the Fama-French 6-factor model, the differences in total factor loadings (*VAL+MOM+INV+PROF*) are not economically meaningful for the full sample (column (5)). Hence, HMFs do not appear to use derivatives to exploit factor returns. Our emphasis on funds with large 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.[24]

[Table 7]

[24] In the Internet Appendix, Table IA-6, we also show that derivative users have significantly lower total factor tilts (*VAL+MOM+INV+PROF;* as inferred from their equity portfolios), compared to non-users.

5.2 Actual Performance, Unobserved Actions, and Fees

To assess the actual performance of factor funds, and in particular the importance of unobserved actions, we shift our focus 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 8. 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 17 bps per month, as measured by CAPM alpha, of multi-factor HMFs with large tilts compared to their ETF counterparts. The corresponding difference between large and contrary tilt HMFs is also unchanged, at 20 bps. 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 discussed earlier, fixed income positions are generally small for HMFs, and derivative use is far lower among funds with large factor tilts. Nevertheless, we drop derivative users from the sample (columns (3)) to ensure robustness, and we find very similar results. Finally, we confirm that large tilt ETFs underperform relative to contrary tilt ETFs by about 8-11 bps per month, regardless of whether we use CAPM or FF6 alphas.

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 large 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)).[25]

[Table 8]

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 risk premia are passed on to them (Berk and van Binsbergen (2015)). When using net returns, the performance differential—as measured by CAPM alpha between multi-factor HMFs and ETFs with large factor tilts—drops by about half to 8 bps per month, but remains significant at the 5% level (column (4)). 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. A more puzzling finding is that the performance gap between large and contrary HMFs is similar (or even stronger) with net returns. Better performing factor 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 (2021b)). It could be that HMFs with contrary tilts charge relatively higher fees because of their increased propensity to use 'complex' strategies requiring

[25] Implementation issues with smart-beta products may also explain the recent debut of active, non-transparent, ETFs that do not have to disclose their holdings daily or follow a pre-determined benchmark (Johnson (2020)).

more time and effort, or because their clientele is less sophisticated. We leave these questions for future research.

5.3 Robustness: Calendar time portfolios and investable benchmarks

In additional analyses reported in the internet appendix (see Table IA-8), we construct calendar time portfolios, where we take long (short) positions in HMFs (ETFs) with large (contrary) factor tilts. Despite the short time-series, we confirm that large tilt HMFs outperform corresponding ETFs by 1.78% (1.34%) per year using holdings-based (gross) returns and CAPM alpha to measure performance. When comparing large to contrary tilt HMFs, the outperformance is even stronger at 3.27% and 2.09% per year for holdings-based and gross returns respectively.

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 investable ETF benchmark as the average returns of ETFs in the same factor tilt category (*contra*, *marginal*, *moderate* or *large*) 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 weights equal to the inverse of the Euclidean spatial distance in factor tilts between a HMF and its peer ETF at q-1, following Hoberg, Kumar and Prabhala (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 9. When using holdings-based returns, the average benchmark-adjusted alpha of large factor tilt HMFs is +13.22 bps per month, while it is -10.47 bps per month for contrary tilt HMFs. The difference between large and contrary tilt HMFs is therefore 23.68 bps per month and it is significant at the 1% level. The corresponding difference remains similar both when using gross returns (18.88 bps) and net returns (20.86 bps). Factor-based HMFs therefore outperform an investable factor benchmark constructed using similar ETFs by a significant margin. These results confirm that a group of HMFs are successful in harvesting the factor-related returns, but investors should be careful in identifying these HMFs that provide the right factor exposure.

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. The inability to deviate from a pre-determined benchmark index suggests that while investors are getting factor exposure, the factor replication ability may disappoint.

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 factor replication ability, we show that HMFs with large factor tilts outperform ETFs with corresponding tilts when using holdings-based returns. We attribute this outperformance to the presence of short positions, factor-related returns, and factor timing, but less to stock-picking ability. The results remain strong using gross returns, suggesting that implementation costs do not eliminate the performance benefit from factor replication. 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. These results call into question the factor-replication ability of smart-beta ETFs. 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.

References

Agarwal, V., Boyson, N. M., & Naik, N. Y. (2009). Hedge funds for retail investors? An examination of hedged mutual funds. *Journal of Financial and Quantitative Analysis*, 44(2), 273-305.

Agarwal, V., Gay, G. D., & Ling, L. (2014). Window dressing in mutual funds. *The Review of Financial Studies*, 27(11), 3133-3170.

Amihud, Y., & Goyenko, R. (2013). Mutual fund's R 2 as predictor of performance. *The Review of Financial Studies*, 26(3), 667-694.

Ang, A., Gorovyy, S., & Van Inwegen, G. B. (2011). Hedge fund leverage. *Journal of Financial Economics*, 102(1), 102-126.

Arnott, R. D., Harvey, C. R., Kalesnik, V., & Linnainmaa, J. T. (2021). Reports of value's death may be greatly exaggerated. *Financial Analysts Journal*, 77(1), 44-67.

Arnott, R., and Kalesnik, V. (2017): Why Factor Tilts Are Not Smart "Smart Beta". Research Affiliates. https://www.researchaffiliates.com/en_us/publications/articles/610-why-factor-tilts-are-not-smart-smart-beta.html

Asness, C. S., Porter, R. B., & Stevens, R. L. (2000). Predicting stock returns using industry-relative firm characteristics. Available at SSRN 213872.

Bandi, F. M., Chaudhuri, S. E., Lo, A. W., & Tamoni, A. (2021). Spectral factor models. J*ournal of Financial Economics*, forthcoming.

Basak, S., Pavlova, A., & Shapiro, A. (2007). Optimal asset allocation and risk shifting in money management. *The Review of Financial Studies*, 20(5), 1583-1621.

Ben-David, I., Franzoni, F., Kim, B., & Moussawi, R. (2021). Competition for Attention in the ETF Space (No. w28369). National Bureau of Economic Research.

Ben-David, I., Li, J., Rossi, A., & Song, Y. (2021a). Ratings-driven demand and systematic price fluctuations. *The Review of Financial Studies*, forthcoming.

Ben-David, I., Li, J., Rossi, A., & Song, Y. (2021b). What do mutual fund investors really care about?. *The Review of Financial Studies*, forthcoming.

Berk, J., and Van Binsbergen, J. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics,* 118(1), 1-20.

Blume, M. E., & Keim, D. B. (2014). The changing nature of institutional stock investing. *Critical Finance Review*, 6, 1-41.

Bowles, B., Reed, A. V., Ringgenberg, M. C., & Thornock, J. R. (2020). Anomaly time. Available at SSRN 3069026.

Boyde, E. (2021): More than 10% of ETFs have made changes to their index, data show, Financial Times, (February 18).

Briere, M., Lehalle, C. A., Nefedova, T., & Raboun, A. (2019). *Stock market liquidity and the trading costs of asset pricing anomalies*. Available at SSRN: https://ssrn.com/abstract=3380239.

Broman, M. S. and Densmore, M. and Shum Nolan, P. (2021): *The Geography of Sub-advisors and its Impact on International Equity Mutual Funds*. Available at SSRN: https://ssrn.com/abstract=3302214.

Brown, D. C., Cederburg, S., & Towner, M. (2020). Dominated ETFs. Available at SSRN.

Brown, K. C., Harlow, W. V., & Starks, L. T. (1996). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance*, 51(1), 85-110.

Buffa, A.,D.Vayanos, and P.Woolley (2015). *Asset management contracts and equilibrium prices*. Working Paper, London School of Economics.

Calluzzo, P., Moneta, F., & Topaloglu, S. (2019). When anomalies are publicized broadly, do institutions trade accordingly?. *Management Science*, 65(10), 4555-4574.

Calluzzo, P., Moneta, F., & Topaloglu, S. (2021). Complex Instrument Allowance at Mutual Funds. *Critical Finance Review* forthcoming.

Chaieb, I., Langlois, H., and Scaillet, O., 2020. Factors and risk premia in individual international stock returns. *Journal of Financial Economics*, forthcoming.

Chakraborty, I., Kumar, A., Muhlhofer, T., & Sastry, R. (2020). Heuristic fund allocation decisions. Available at SSRN: https://ssrn.com/abstract=2869426.

Chen, A. Y., & Velikov, M. (2019). Zeroing in on the Expected Returns of Anomalies. *Journal of Financial and Quantitative Analysis*, forthcoming.

Chen, H., Desai, H., & Krishnamurthy, S. (2013). A first look at mutual funds that use short sales. *Journal of Financial and Quantitative Analysis*, 48(3), 761-787.

Chen, Q., Goldstein, I., & Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2), 239-262.

Choi, D., Kahraman, B., & Mukherjee, A. (2016). Learning about mutual fund managers. *The Journal of Finance*, 71(6), 2809-2860.

Christoffersen, S. E., & Simutin, M. (2017). On the demand for high-beta stocks: Evidence from mutual funds. *The Review of Financial Studies*, 30(8), 2596-2620.

Cohen, R. B., Polk, C., & Vuolteenaho, T. (2003). The value spread. *The Journal of Finance*, 58(2), 609-641.

Cui, X., Kolokolova, O., & Wang, G. J. (2020). On the Other Side of Hedge Fund Equity Trades. Available at SSRN 3304606.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic‐based benchmarks. *The Journal of finance*, 52(3), 1035-1058.

Daniel, K., Mota, L., Rottke, S., & Santos, T. (2020). The cross-section of risk and returns. *The Review of Financial Studies*, 33(5), 1927-1979.

Del Guercio, D. (1996). The distorting effect of the prudent-man laws on institutional equity investments. *Journal of Financial Economics*, 40(1), 31-62.

DeMiguel, V., Martin-Utrera, A., & Uppal, R. (2019). What Alleviates Crowding in Factor Investing?. Available at SSRN 3392875.

Dimson, E. (1979): Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics,* 7, 197–226.

Drechsler, I., & Drechsler, Q. F. (2014). The shorting premium and asset pricing anomalies (No. w20282). National Bureau of Economic Research.

Easley, D., Michayluk, D., O'Hara, M., & Putniņš, T. J. (2021). The active world of passive investing. Review of Finance, 25(5), 1433-1471.

Edelen, R. M., Ince, O. S., & Kadlec, G. B. (2016). Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119(3), 472-488.

Ehsani, S. and Linnainmaa, J.T. (2021): *Time-Series Efficient Factors.* Available at SSRN: https://ssrn.com/abstract=3555473.

Ehsani, S., & Linnainmaa, J. T. (2021). Factor momentum and the momentum factor. *Journal of Finance*, forthcoming.

Eisfeldt, A. L., Kim, E., & Papanikolaou, D. (2021). Intangible value. Available at SSRN.

Evans, R.B. and Sun, Y. (2021): Models or Stars: The Role of Asset Pricing Models and Heuristics in Investor Risk Adjustment, *The Review of Financial Studies*, 34 (1), 67–107.

Falkenstein, E. G. (1996). Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *The Journal of Finance*, 51(1), 111-135.

Fama, E. F., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2), 427-465.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics,* 116(1), 1-22.

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of financial economics*, 128(2), 234-252.

Flood, Chris, 2019, Investors' smart money piles into smart beta ETFs, Financial Times (February 11).

Frazzini, A., Israel, R., & Moskowitz, T. J. (2018). Trading costs. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3229719.

Gao, Xin and Wang, Ying (2021). Mining the Short Side: Institutional Investors and Stock Market Anomalies. *Journal of Financial and Quantitative Analysis*, forthcoming.

Gilbert, T., Hrdlicka, C., Kalodimos, J., & Siegel, S. (2014). Daily data is bad for beta: Opacity and frequency-dependent betas. *The Review of Asset Pricing Studies,* 4(1), 78-117.

Golubov, A., & Konstantinidi, T. (2019). Where Is the Risk in Value? Evidence from a Market-to-Book Decomposition. *The Journal of Finance*, 74(6), 3135-3186.

Grinblatt, M., & Saxena, K. (2018). When Factors Do Not Span Their Basis Portfolios. *Journal of Financial and Quantitative Analysis*, 53(6), 2335-2354.

He, Z., & Xiong, W. (2013). Delegated asset management, investment mandates, and capital immobility. *Journal of Financial Economics*, 107(2), 239-258.

Hoberg, G., Kumar, N., & Prabhala, N. (2018). Mutual fund competition, managerial skill, and alpha persistence. *The Review of Financial Studies*, 31(5), 1896-1929.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies*, 33(5), 2019-2133.

Huang, J. Z., & Wang, Y. (2013). Should investors invest in hedge fund-like mutual funds? Evidence from the 2007 financial crisis. *Journal of Financial Intermediation*, 22(3), 482-512.

Huang, S., Song, Y., & Xiang, H. (2020). The smart beta mirage. Available at SSRN 3622753.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1), 65-91.

Jiang, G. J., Yao, T., & Yu, T. (2007). Do mutual funds time the market? Evidence from portfolio holdings. *Journal of Financial Economic*s, 86(3), 724-758.

Johnson, Ben (2014). A Sensible Approach to 'Smart Beta'. https://www.morningstar.com/articles/647771/a-sensible-approach-to-smart-beta

Johnson, Ben (2020). Active Non-Transparent ETFs: What Are They Good For? Morningstar (July, 28). https://www.morningstar.com/articles/993801/active-non-transparent-etfs-what-are-they-good-for

Johnson, Ben (2021). FTSE Russell to review $9tn US index shake-up (July, 19). https://www.ft.com/content/15c320bc-ca95-417c-8bff-ed0dce327aa7

Jordan, B. D., & Riley, T. B. (2015). Volatility and mutual fund manager skill. Journal of Financial Economics, 118(2), 289-298.

Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). Time-varying fund manager skill. The *Journal of Finance*, 69(4), 1455-1484.

Kacperczyk, M., Sialm, C., & Zheng, L. (2008). Unobserved actions of mutual funds. *The Review of Financial Studies*, 21(6), 2379-2416.

Kamara, A., Korajczyk, R. A., Lou, X., Sadka, R., 2016. Horizon pricing. *Journal of Financial and Quantitative Analysis* 51, 1769{1793.

Kempf, A., Ruenzi, S., & Thiele, T. (2009). Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry. *Journal of Financial Economics*, 92(1), 92-108.

Khan, M., Kogan, L., Serafeim, G., 2012. Mutual fund trading pressure: firm-level stock price impact and timing of SEOs. *Journal of Finance* 67, 1371-1395.

Lee, J. H., Trzcinka, C., & Venkatesan, S. (2019). Do portfolio manager contracts contract portfolio management?. *The Journal of Finance*, 74(5), 2543-2577.

Lettau, M., Ludvigson, S. C., & Manoel, P. (2021). *Characteristics of mutual fund portfolios: where are the value funds?*. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3306086

Lewellen, J. (2011). Institutional investors and the limits of arbitrage. *Journal of Financial Economics*, 102(1), 62-80.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of financial studies*, 25(12), 3457-3489.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2015). Scale and skill in active management. *Journal of Financial Economics*, 116(1), 23-45.

Ma, L., Tang, Y., & Gomez, J. P. (2019). Portfolio manager compensation in the US mutual fund industry. *The Journal of Finance*, 74(2), 587-638.

Malkiel, B. G. (2014). Is smart beta really smart?. *The Journal of Portfolio Management*, 40(5), 127-134.

Novy-Marx, R. & and Velikov, M. (2016): A taxonomy of anomalies and their trading costs, *Review of Financial Studies,* 29, 104-147.

Novy-Marx, R., & Velikov, M. (2021). Betting against betting against beta. *Journal of Financial Economics*.

Pastor, L., Stambaugh, R., and Taylor, L., 2015. Scale and skill in active management. *Journal of Financial Economics*, 116(1), 23-45.

Patton, A. J., & Weller, B. M. (2020). What you see is not what you get: The costs of trading market anomalies. *Journal of Financial Economics*, 137(2), 515-549.

Puckett, A., & Yan, X. (2011). The interim trading skills of institutional investors. *The Journal of Finance,* 66(2), 601-633.

Rajan, Amin, 2019. Alternative risk premia will be tested in the next downturn, Financial Times (November 4).

Riding, Siobhan, 2018, Smart beta moves into mainstream for large investors, Financial Times (November 5).

Riding, Siobhan, 2020. Alternative risk premia funds fail to live up to expectations, Financial Times (April 27).

Sensoy, B. A. (2009). Performance evaluation and self-designated benchmark indexes in the mutual fund industry. *Journal of Financial Economics*, 92(1), 25-39.

Simutin, M. (2014). Cash holdings and mutual fund performance. *Review of Finance*, 18(4), 1425-1464.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2), 288-302.

Wigglesworth, Robin, 2018. Can factor investing kill off the hedge fund? Financial Times (July 22).

Table 1: Summary Statistics

This table presents summary statistics for Hedged mutual funds (HMFs) and factor-based Exchange-Traded Funds (ETFs). *#Funds* is the number of unique funds, Assets Under Management (*AUM*) is the total fund size of a fund 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 and leverage ratios are in percentages. Panel A summarizes the results for HMFs by (static) Morningstar Categories over the 2006-2019 sample period. Panel B provides the results by ETFs that are actively managed and by Morningstar's Strategic Beta Category (with the additional Factor Value category) over the 2010-2019 sample period.

		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								
Morningstar Category								
Leveraged Net Long	19	904.30	120.60	1.27	184.72	122.32	24.84	0.37
Long-Short Equity	117	371.60	81.70	1.74	288.21	85.29	30.97	3.20
Market Neutral	45	838.70	225.80	1.49	285.23	83.91	51.50	8.16
Multi-alternative	49	460.48	168.85	1.71	253.71	62.14	18.86	18.09
Options-based	37	650.96	80.90	1.18	94.44	90.42	2.30	4.13
Panel B: Factor-based ETFs								
Strategic Beta Category								
Momentum	13	725.54	91.40	0.42	92.30	99.84		
Quality	29	3007.18	283.70	0.34	47.72	99.86		
Factor Value	9	517.99	141.70	0.29	40.57	99.45		
Standard Value	27	5215.79	927.67	0.20	32.41	99.93		
Dividend yielding	42	2635.32	647.50	0.37	42.65	99.61		
Fund.-weighted	14	887.36	343.04	0.39	26.53	99.80		
Growth	30	5190.00	879.56	0.22	38.38	99.74		
Low Risk	15	2045.83	191.80	0.27	56.36	99.68		
Multi-Factor	65	287.54	111.15	0.51	97.78	99.68		
Actively managed	43	87.27	59.60	0.75	169.72	96.16		

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) valuation, ii) momentum (*t*-2, *t*-12), iii) asset growth, and iv) operating profitability (additional details can be found in Appendix 1). 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 valuation ratio of fund *i* at time *t* is the portfolio-weighted average of the valuation 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: $(C_{i,t} - C_{m,t})$. We reverse the order for asset growth, so that higher values indicate conservative (lower) asset growth (and higher expected returns). The column labelled "portfolio" denotes the factor tilt for the complete portfolio. It is calculated by weighting the long and short-side factor tilts by the percentage of AUM invested in long or short positions: $w_{i,t}^{+}(C_{i,t}^{+} - C_{m,t}) + w_{i,t}^{-}(C_{i,t}^{-} - C_{m,t})$. E.g., for a 130/30 fund, the long side receives 130 % weight and the short-side receives -30% weight. The column long-short is the simple difference between $(C_{i,t}^{+} - C_{m,t})$ and $(C_{i,t}^{-} - C_{m,t})$, i.e., it does not account for the weight invested. Panel A (B) [C] presents the results for HMFs (newer generation of smart-beta ETFs) [older generation of smart-beta ETFs]. The sample period for HMFs (ETFs) is 01/2006 (01/2010) to 12/2019. */**/*** 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

	Value (VAL)				Momentum (MOM)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.403***	0.630***	0.361***	-0.218***	0.262***	0.850***	0.051	-0.711***
	(8.68)	(7.86)	(8.70)	(5.07)	(4.78)	(8.51)	(1.07)	(10.59)
Nobs	4,839	3,172	4,627	3,384	4,839	3,172	4,627	3,384
	Conservative Asset Growth (CAG)				Profitability (PROF)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.271***	0.522***	0.115***	-0.450***	0.108**	0.397***	-0.151***	-0.670***
	(6.24)	(5.99)	(3.24)	(7.88)	(2.20)	(3.91)	(3.20)	(8.76)
Nobs	4,839	3,172	4,627	3,384	4,839	3,172	4,627	3,384

	Total Factor tilt (VAL+MOM+CAG+PROF)			
	Portfolio	Long-Short	Long	Short
Average	1.044***	1.792***	0.376***	-2.049***
	(6.99)	(8.66)	(3.47)	(10.96)
Nobs	4,839	4,839	4,627	3,384

Panel B: Newer generation of smart-beta ETFs					
	VAL	MOM	CAG	PROF	Total Factor tilt
	(1)	(2)	(3)	(4)	(1-4)
Actively managed					
Average	0.511***	0.118	0.312**	0.135	1.076***
	(3.29)	(1.54)	(2.23)	(1.25)	(3.04)
Nobs	441	441	441	441	441
Multi Factor					
Average	0.742***	0.106	0.196**	-0.011	1.033***
	(4.70)	(0.70)	(2.22)	(0.11)	(6.28)
Nobs	1,038	1,038	1,038	1,038	1,038
Momentum					
Average	-0.735***	1.376***	-0.517***	0.081	0.204
	(5.03)	(5.57)	(4.91)	(0.59)	(0.53)
Nobs	292	292	292	292	292
Quality					
Average	-0.171	-0.275**	0.605***	1.025***	1.185***
	(1.70)	(2.24)	(7.31)	(6.02)	(4.13)
Nobs	363	363	363	363	363
Factor value					
Average	2.297***	-0.946***	0.774***	-0.418	1.706***
	(10.20)	(5.60)	(8.71)	(1.71)	(11.98)
Nobs	138	138	138	138	138

Panel C: Older generation of smart-beta ETFs					
	VAL	MOM	CAG	PROF	Total Factor tilt
	(1)	(2)	(3)	(4)	(1-4)
Standard value					
Average	1.135***	-0.473***	0.465***	-0.454***	0.672***
	(21.80)	(13.67)	(7.83)	(4.27)	(3.66)
Nobs	930	930	930	930	930
Dividend yielding					
Average	0.658***	-0.591***	0.472***	0.245**	0.784***
	(8.32)	(11.00)	(8.68)	(2.65)	(5.71)
Nobs	893	893	893	893	893
Fundamentally-weighted					
Average	0.980***	-0.405***	0.424***	0.216	1.215***
	(8.35)	(8.66)	(4.75)	(1.43)	(6.21)
Nobs	385	385	385	385	385
Growth					
Average	-1.049***	0.561***	-0.411***	0.485***	-0.414**
	(21.67)	(10.79)	(8.79)	(5.15)	(2.52)
Nobs	1,052	1,052	1,052	1,052	1,052

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 having a *contrary* factor tilt if the total factor tilt is negative; a *marginal* factor tilt is a portfolio where -0.5 < total factor tilt < 0.5 deciles; a *moderate* factor tilt is a portfolio with 0.5 ≤ total factor tilt < 1.5 deciles; a large factor tilt is a portfolio with a total factor tilt ≥ 1.5. 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: $\left(C_{i,t}^{Value} - C_{M,t}^{Value}\right) + \left(C_{i,t}^{Mom} - C_{M,t}^{Mom}\right) + \left(C_{i,t}^{CAG} - C_{M,t}^{CAG}\right) + \left(C_{i,t}^{Prof} - C_{M,t}^{Prof}\right)$. 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, separately for the fund's long and short positions and for the difference (long-minus-short). Panel B summarizes the results for factor-based ETFs. The sample period for HMFs (ETFs) is 01/2006 (01/2010) to 12/2019. */**/*** 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	Long	Short	Portfolio	Long-Short	Long	Short
Average	-1.300***	-1.199***	-1.721***	-0.623**	0.062**	0.276***	-0.035	-0.531***
	(7.96)	(7.38)	(8.08)	(2.28)	(2.32)	(4.25)	(0.85)	(4.20)
Nobs	829	829	807	634	1,291	1,291	1,238	754

	Moderate Factor Tilt (q-1)				Large Factor Tilt (q-1)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.870***	1.562***	0.765***	-1.496***	3.500***	5.144***	1.801***	-3.910***
	(24.32)	(11.83)	(14.49)	(7.07)	(21.74)	(22.86)	(20.25)	(20.03)
Nobs	920	920	869	516	1,434	1,434	1,384	1,249

Panel B: Factor-based ETFs

	Active/multi-factor ETFs				Single-Factor ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-1.526***	0.121**	1.014***	2.363***	-1.196***	0.127***	0.941***	1.932***
	(3.54)	(2.57)	(21.61)	(19.15)	(11.66)	(3.71)	(30.53)	(31.84)
Nobs	168	280	382	525	830	1,143	1,251	883

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 (*contrary*, *marginal*, *moderate*, or *large*). 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 *contrary* if the total factor tilt is negative; a *marginal* factor tilt is a portfolio with -0.5 < total factor tilt < +0.5 deciles; a *moderate* factor tilt is a portfolio with 0.5 ≤ total factor tilt < 1.5 deciles; a *large* factor tilt is a portfolio where the total factor tilt ≥ 1.5. The total factor tilt is calculated based on the sum of value, momentum, conservative asset growth, and profitability tilts. For the short sub-portfolio, we reverse the signs because negative factor tilts (relative to the market) are expected if the fund is betting on anomalies with low expected returns. Portfolios with a meaningful factor tilt (moderate or large) 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 for HMFs (ETFs) is 01/2006 (01/2010) to 12/2019. %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.				
Contrary tilt	**18.49**	83.70	26.62	**22.92**	**13.43**	**13.11**	**20.21**
Single (>75%)	8.57	85.17	26.32	11.42	6.35	9.15	14.49
Multi (≤75%)	9.92	82.42	26.89	11.50	7.08	3.97	5.71
Marginal tilt	**29.55**	78.68	19.13	**28.59**	**16.76**	**20.17**	**27.58**
Moderate tilt	**20.54**	81.72	18.34	**25.17**	**17.06**	**27.98**	**30.65**
Single (>75%)	10.18	86.07	20.55	13.65	10.13	16.61	23.16
Multi (≤75%)	10.37	77.44	16.18	11.53	6.93	11.37	7.49
Large tilt	**31.41**	99.68	46.44	**23.32**	**52.75**	**38.74**	**21.56**
Single (>75%)	2.26	94.92	37.54	2.69	6.11	9.55	6.98
Multi (≤75%)	29.15	100.05	47.13	20.62	46.64	29.19	14.59

Table 5: Factor Tilts Relative to Factor Benchmarks

This table presents average factor tilts relative to factor benchmarks. Fund-level characteristics are constructed by value-weighting the stocks in a fund's portfolio, e.g., the valuation ratio of a fund is the portfolio-weighted average of the valuation 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 a benchmark portfolio. In Panel A, the benchmark portfolio for the fund's long positions is a value-weighted portfolio that takes positions in the top tercile on a stock characteristic. Here we present the results only for the fund's largest factor tilt (e.g., value tilt for fund A in quarter *q*, and momentum tilt for fund B in quarter *q*). In Panel B, we use instead 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 for HMFs (ETFs) is 01/2006 (01/2010) to 12/2019. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (*t*-statistics in brackets).

Panel A: Largest factor tilt relative to a single-factor benchmark

	Value tilt of Standard Value, Dividend yielding, Fundamentally-weighted ETFs			Value tilt of Factor Value ETFs		
	Full Sample	Large tilt	Large tilt & Single (max tilt >75%)	Full Sample	Large tilt	Large tilt & Single (max tilt >75%)
ETF portfolio: Expected sign (+)						
Average	-2.128***	-1.940***	-1.476***	-0.768*	-0.590	-0.354
	(33.49)	(16.39)	(7.55)	(2.29)	(1.66)	(1.29)
Nobs	2,208	576	97	138	70	54

	Momentum tilt of Momentum ETFs			Profitability tilt of Quality ETFs		
	Full Sample	Large tilt	Large tilt & Single (max tilt >75%)	Full Sample	Large tilt	Large tilt & Single (max tilt >75%)
ETF portfolio: Expected sign (+)						
Average	-0.562*	0.008	0.316	-1.093***	-0.615***	-0.416***
	(2.06)	(0.02)	(1.17)	(6.68)	(8.14)	(7.07)
Nobs	292	66	52	363	166	73

Panel B: Total factor tilts relative to a multi-factor benchmark					
		Moderate tilt		Large tilt	
	Full sample	Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
HMF complete portfolio: Expected sign (+)					
Average	-1.708***	-1.593***	-1.161***	-1.218***	0.087
	(12.84)	(18.34)	(13.22)	(6.08)	(0.57)
Nobs	4,839	493	496	110	1,406
HMF long sub-portfolio: Expected sign (+)					
Average	-1.840***	-1.473***	-1.200***	-0.859***	-0.319***
	(16.72)	(24.93)	(18.56)	(4.95)	(3.55)
Nobs	4,627	480	452	108	1,356
HMF short sub-portfolio: Expected sign (-)					
Average	0.982***	1.570***	1.399***	0.901**	-1.014***
	(5.20)	(8.41)	(4.79)	(2.35)	(5.10)
Nobs	3,384	291	243	81	1,250

	Active/multi-factor labelled ETFs				
		Moderate tilt		Large tilt	
	Full sample	Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
Expected sign (+)					
Average	-1.196***	-1.260***	-1.182***	-0.422***	0.292*
	(7.94)	(17.83)	(13.90)	(3.16)	(1.73)
Nobs	1,479	243	168	141	432
	Single-factor labeled ETFs				
		Moderate tilt		Large tilt	
	Full sample	Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
Expected sign (+)					
Average	-1.819***	-1.358***	-1.075***	-0.389***	-0.128
	(19.32)	(27.29)	(11.48)	(4.40)	(1.46)
Nobs	4,316	997	322	302	624

Table 6: 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*, *moderate,* and *large*), interacted with a dummy for HMFs. The omitted (benchmark) group consists of HMFs/ETFs with marginal factor tilts. Columns (1), (3), and (5) in Panel A and columns (1), (3), (5), and (7) in Panel B are estimated for the full sample of funds, while columns (2), (4) and (6) in Panel A and columns (2), (4), (5), and (8) 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 and Fama-French 6 factor alpha for holdings-based returns in Panel A (with betas estimated using daily data in the prior quarter), and by DGTW characteristic-adjusted returns or characteristic timing in Panel B. Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2019. */**/*** 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	-0.0075	0.0100	0.0481*	0.0329	-0.0129	-0.0046
	(0.23)	(0.15)	(1.88)	(0.55)	(0.40)	(0.07)
× HMF	-0.0499	-0.1068	-0.0795**	-0.0758	-0.0430	-0.0911
	(1.13)	(1.33)	(2.04)	(1.05)	(0.99)	(1.12)
Moderate tilt	0.0566**	0.0606	0.0575***	0.0598***	0.0522*	0.0461
	(2.06)	(1.50)	(3.85)	(2.65)	(1.92)	(1.18)
× HMF	-0.0205	-0.0040	-0.0796***	-0.0564**	-0.0002	0.0306
	(0.67)	(0.09)	(3.61)	(2.00)	(0.01)	(0.73)
Large tilt	-0.0843**	-0.0745**	-0.0014	-0.0150	-0.0859**	-0.0774**
	(2.48)	(2.26)	(0.07)	(0.74)	(2.56)	(2.38)
× HMF	0.1793***	0.1820***	-0.0116	0.0034	0.0343	0.0310
	(4.77)	(4.75)	(0.37)	(0.10)	(0.95)	(0.84)
Large – Contrary (ETF)	-0.0767*	-0.0845	-0.0495	-0.0479	-0.0730*	-0.0728
Large – Contrary (HMF)	0.1526***	0.2043***	0.0184	0.0313	0.0043	0.0492
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	0.077	0.065	0.047	0.048	0.118	0.112
N	31,224	21,287	31,224	21,287	30,681	20,807

Panel B: DGTW characteristic-adjusted returns and characteristic timing								
	Complete equity portfolio				Long-side sub-portfolio			
	Char-adj Return		Timing Return		Char-adj Return		Timing Return	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contrary	0.0493*	0.1211*	0.0051	0.0367**	0.0486*	0.1165*	0.0024	0.0317*
	(1.95)	(1.83)	(0.40)	(1.97)	(1.94)	(1.79)	(0.19)	(1.69)
× HMF	-0.0725*	-0.1527**	0.0018	-0.0551**	-0.0959**	-0.1567**	-0.0028	-0.0528*
	(1.92)	(2.00)	(0.09)	(1.99)	(2.49)	(1.99)	(0.15)	(1.89)
Moderate tilt	0.0051	-0.0217	0.0021	0.0053	0.0060	-0.0254	-0.0017	0.0011
	(0.34)	(0.99)	(0.24)	(0.42)	(0.40)	(1.15)	(0.19)	(0.08)
× HMF	-0.0099	0.0189	-0.0072	-0.0113	-0.0230	0.0106	0.0047	0.0054
	(0.44)	(0.65)	(0.53)	(0.68)	(0.98)	(0.36)	(0.35)	(0.32)
Large tilt	-0.0147	-0.0324*	0.0198*	0.0077	-0.0124	-0.0315*	0.0175	0.0050
	(0.88)	(1.75)	(1.70)	(0.71)	(0.74)	(1.70)	(1.49)	(0.47)
× HMF	0.0558**	0.0850***	0.0271**	0.0368***	-0.0039	0.0256	0.0168	0.0249**
	(2.13)	(3.04)	(1.97)	(2.78)	(0.18)	(1.10)	(1.23)	(1.97)
Large – Contrary (ETF)	-0.0639**	-0.1535**	0.0147	-0.0289	-0.0610**	-0.1479**	0.0151	-0.0267
Large – Contrary (HMF)	0.0644*	0.0843*	0.0400**	0.0629***	0.0310	0.0343	0.0347*	0.0510**
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Full	Multi factor	Full	Multi factor	Full	Multi factor
Fixed effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.054	0.061	0.028	0.031	0.053	0.056	0.038	0.038
N	31,221	20,914	28,101	18,867	30,680	20,438	27,558	18,396

Table 7: Factor Exposures and Derivative Use

This table reports the results for pooled OLS regressions of fund-quarter total factor exposures on factor classification dummies (*contrary*, *marginal*, *moderate* × *single*, *moderate* × *multi, large* × *single*, or *large* × *multi*) 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 (5)), and for sub-samples that exclude derivative users (no options, futures or swaps; *#Deriv.* = 0, columns (2) and (6)), or excluding Morningstar Categories associated with derivative use (option-based, or multi-alternative; columns (3), (4), (7), and (8)). The sample period is from 01/2006 to 12/2019. */**/*** 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)	(5)	(6)	(7)	(8)
Contra/Marginal	-0.125***	-0.080***	-0.067***	-0.064***	0.013*	0.020*	0.015*	0.018
	(6.63)	(3.11)	(4.80)	(4.33)	(1.78)	(1.73)	(1.67)	(1.62)
Moderate × Single	-0.127***	-0.058**	-0.107***	-0.114***	0.001	0.012	0.010	0.009
	(4.37)	(2.41)	(3.51)	(3.45)	(0.13)	(0.87)	(1.03)	(0.88)
Moderate × Multi	-0.114***	-0.049*	-0.031	-0.031	-0.044***	-0.026	-0.050**	-0.049**
	(2.78)	(1.81)	(0.87)	(0.71)	(2.68)	(1.34)	(2.48)	(2.00)
Large × Single	-0.121***	-0.039	-0.070**	-0.069**	0.001	0.049**	0.027	0.027
	(2.96)	(1.40)	(2.36)	(2.28)	(0.06)	(2.17)	(1.42)	(1.41)
Large × Multi	-0.041	-0.002	-0.020	-0.021	0.015	0.024***	0.014	0.012
	(1.17)	(0.16)	(0.57)	(0.58)	(1.14)	(3.02)	(1.03)	(0.83)
Sample	Full	#Deriv. = 0	MC ≠ Opt.	MC ≠ Opt. MC ≠ Multi	Full	#Deriv. = 0	MC ≠ Opt.	MC ≠ Opt. MC ≠ Multi
Adj. R^2	0.131	0.074	0.057	0.054	0.004	0.009	0.005	0.005
Nobs	4,477	2,186	3,825	3,291	4,453	2,173	3,803	3,268

Table 8: 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*, *moderate,* and *large*), interacted with a dummy for HMFs. The omitted (benchmark) group consists of HMFs/ETFs with marginal factor tilts. Columns (1), (2), (3), (5), and (6) are estimated for gross returns, while column (4) is 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) and (5)), for multi-factor funds (columns (2), (4), and (6)), and for the sub-sample that excludes derivative users in column (3). Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2019. */**/*** 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	-0.0130	-0.0128	0.0108	0.0416	0.0448	0.0478	0.0472	0.0089
	(0.35)	(0.16)	(0.13)	(1.15)	(0.56)	(0.58)	(1.53)	(0.12)
× HMF	-0.0484	-0.1158	-0.1154	-0.1627***	-0.2433***	-0.2435*	-0.0757	-0.0805
	(0.92)	(1.22)	(0.90)	(3.09)	(2.60)	(1.89)	(1.58)	(0.95)
Moderate tilt	0.0528*	0.0644	0.0853*	0.1077***	0.1094***	0.1095**	0.0433**	0.0480**
	(1.85)	(1.54)	(1.93)	(3.80)	(2.62)	(2.47)	(2.57)	(2.12)
× HMF	-0.0249	-0.0295	-0.1288*	-0.1199***	-0.1135**	-0.2118***	-0.0629**	-0.0520
	(0.68)	(0.56)	(1.83)	(3.25)	(2.18)	(3.05)	(1.98)	(1.28)
Large tilt	-0.0993***	-0.0968***	-0.0687*	-0.0530	-0.0553	-0.0485	-0.0359*	-0.0552**
	(2.83)	(2.72)	(1.77)	(1.49)	(1.55)	(1.24)	(1.73)	(2.55)
× HMF	0.1497***	0.1640***	0.1516***	0.0616	0.0747*	0.0640	-0.0152	0.0061
	(3.88)	(4.19)	(3.75)	(1.59)	(1.92)	(1.59)	(0.54)	(0.21)
Large – Contrary (ETF)	-0.0863*	-0.0839	-0.0795	-0.0945**	-0.1001	-0.0963	-0.0831**	-0.0641
Large – Contrary (HMF)	0.1118**	0.1959***	0.1875*	0.1297***	0.2179***	0.2113**	-0.0226	0.0225
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Multi factor & #Deriv. = 0	Full	Multi factor	Multi factor & #Deriv. = 0	Full	Multi factor
Fixed effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.058	0.050	0.085	0.058	0.050	0.084	0.036	0.038
N	33,469	21,107	15,688	33,673	21,232	15,813	33,469	21,107

Table 9: 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*, *moderate* or *large*). 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 12/2019. Standard errors are clustered by fund (*t*-statistics in brackets).

	Holdings-based return	Actual (gross) return	Actual (net) returns
	(1)	(2)	(3)
Intercepts:			
Contrary tilt	-0.1047**	-0.1061*	-0.1207**
	(2.24)	(1.79)	(2.05)
Moderate tilt	-0.0369	0.0013	0.0047
	(0.84)	(0.03)	(0.10)
Large tilt	0.1322***	0.0826**	0.0879**
	(3.70)	(2.20)	(2.35)
Difference: Large – Contrary	0.2369***	0.1887***	0.2086***
	(5.25)	(3.06)	(3.39)
Betas:			
Inv. ETF BMK return	0.5610***	0.4213***	0.4212***
	(16.25)	(13.74)	(13.73)
× Contrary	-0.0234	0.0497	0.0500
	(0.66)	(1.26)	(1.27)
× Moderate	0.0217	-0.0169	-0.0169
	(0.52)	(0.42)	(0.42)
× Large	-0.0669	0.0265	0.0269
	(0.94)	(0.37)	(0.38)
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt
Adj. R^2	0.509	0.384	0.384
N	13,338	13,254	13,254

Appendix 1: Variable descriptions

Variable	Definition
Size (Market capitalization)	The natural logarithm of stock *j*'s market capitalization.
Momentum	The cumulative return of a stock from month *t*-2 to month *t*-12 (i.e., skipping the most recent month).
Valuation ratios	
B/M ratio	The ratio of stock *j*'s book equity at the end of its fiscal year to its December end market capitalization. Following Fama and French (1993), among others, book equity is Compustat book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, I use the redemption, liquidation, or par value (in that order) to estimate the value of preferred stock. If common equity is not available, I replace it with total asset minus liability minus preferred equity (if available).
S/P ratio	The ratio of stock *j*'s sales at the end of its fiscal year to its December end market capitalization.
E/P ratio	The ratio of stock *j*'s Net Income at the end of its fiscal year to its December end market capitalization.
CF/P ratio	The ratio of stock *j*'s Cash-flows from operations at the end of its fiscal year to its December end market capitalization. Following Gutiérrez and Philippon (2016), the cash flow from operations is defined as the sum of Net Income (IBC), Depreciation and Amortization (DPC), Deferred Taxes (TXDC), Equity in Net Loss (ESUBC), Sale of Property, Plant and Equipment and Investments (SPPIV) and Funds from Operations (FOPO).
Asset Growth	
Total Asset growth	As in Cooper, Gulen, and Schill (2008), the total asset growth rate (TAG) of company j in in June is defined as the natural logarithm of the ratio of its total asset at the end of its most recent fiscal year (December *t*-6), to its total asset in at the end of the prior fiscal year (December *t*-18). Total asset is measured as of the fiscal-year end: $TAG_{j,t} = ln\left(\frac{Total\ Assets_{j,t-6}}{Total\ Assets_{j,t-18}}\right)$
Net Equity issuance	(Net) Equity issuance (NEI) for company *j* in June is defined as the natural logarithm of the annual change in split-adjusted shares outstanding from December (*t*-6) to the prior December (*t*-18). The formula is: $NEI_{j,t} = ln\left(\frac{Shares\ Outs._{j,t-6} \times Cum.Adj.Factor_{j,t-6}}{Shares\ Outs._{j,t-18} \times Cum.Adj.Factor_{j,t-18}}\right)$
Profitability	
Operating profitability	Following Fama and French (2015), operating profitability (OP) for company *j* in June is defined as sales minus cost of goods sold, minus selling, general and administrative expenses, minus interest expense, all divided by the book value of equity.

Appendix 2: 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 et al. (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).

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, Stambaugh and Taylor (2015) find that 3.1 percent 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 bp per month. In our raw sample of hedged mutual funds, the proportion of monthly returns that are inconsistent is only 0.47 percent. The lower proportion of inconsistent returns is likely a consequence of greater data accuracy in more recent years (our sample starts in 2006). Nevertheless, we follow Berk and Binsbergen (2015), and Pastor, Stambaugh and Taylor (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.

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

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

If cases where the dividend data is 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 ($k \in [1,4]$):

$$Factor\ Tilt_{i,q}^{a} = a_0 + b_1 Factor\ Tilt_{i,q-k}^{a} + \varepsilon_{i,q}^{a} \tag{IA1}$$

Our focus is on multi-factor funds with large factor tilts, because this is arguably the more relevant sample for studying variations across factor tilts. As shown in Table IA-3 in the Internet Appendix 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 0.859, while it ranges from 0.687 for momentum to 0.784 for profitability. The simple average of b_1, across the four individual tilts, is 0.724. By contrast, the individual factor tilts of ETFs are far more persistent (b_1 between 0.749 and 0.967) than the total factor tilt (0.626). 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 (2021)). Indeed, we confirm in unreported tests that these ETFs (large factor tilt & multi-factor focus) do not have any significant exposure to the momentum factor, while corresponding HMFs have roughly equal exposure to all four factors, including momentum.

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 in the Internet Appendix show, the off-diagonal elements are in most cases more than twice as large for HMFs compared to ETFs, indicating that the individual factor tilts of HMFs exhibit more time-series variation.

IA.4 Factor Tilts and Derivative Use

To address the concern that our emphasis on HMFs with large factor tilts is likely to capture funds that also use derivatives, we start by estimating regressions of total factor tilts on lagged derivative use and fund characteristics. The first three columns of Table IA-6, Panel A, include dummies for derivative users by type—futures, options, and swaps, as identified by the Morningstar holdings type variable—one at a time. Funds that use options or swaps have significantly lower total factor tilts, by 1.4 and 0.6 deciles respectively. The point estimates drop by more than half if we control for gross equity leverage (column (5)), which is likely explained by the fact that derivative users typically do not have high equity leverage in the first place. Nevertheless, option users continue to have lower total factor tilts by about 0.7 deciles even after controlling for leverage (column (6)). The results remain unchanged even if we drop HMFs in the options-based Morningstar category which use options by definition.

IA.5 Multi-factor picking and factor tilting performance

As a specific measure of a fund's ability to replicate the performance of factor strategies, we modify the "Timing" measure by Kacperczyk et al. (2014) to include other factors besides the market. Specifically, we measure the performance from factor tilting as follows:

$$Tilting_{i,t} = \sum_{j=1}^{N_M} (w_{j,t-1}^{i} - w_{j,t-1}^{m})(FRR_{j,t}) \qquad \text{(IA2)}$$

$$where\ FRR_{j,t}$$

$$= \beta_{j,t-1}^{m} R_t^m + \beta_{j,t-1}^{s} SMB_t + \beta_{j,t-1}^{h} HML_t + \beta_{j,t-1}^{w} WML_t + \beta_{j,t-1}^{c} CMA_t + \beta_{j,t-1}^{r} RMW_t$$

and w_j^i is the weight of stock j in fund i and w_j^m is the corresponding weight in the market portfolio (iShares Russell 3000). Eq. (IA2) captures the returns associated with tilting towards stocks with high factor-related returns. We continue to use the holdings-based approach for computing the factor loadings. Note that the summation is done over all securities in the market portfolio (N_M), which is similar to how active share is computed.[26] Eq. (IA2) is computed separately for the fund's long and short positions, and the complete long-short tilting performance is the weighted average of the two, with the weights given by the percentage of AUM invested in long ($w_i^+ > 0$) or short ($w_i^- < 0$) positions:

$$Tilting_{i,t} = w_{i,t-1}^{+} Tilting_{i,t}^{+} + w_{i,t-1}^{-} Tilting_{i,t}^{-} \tag{IA3}$$

Since the capital invested in long positions is positive, possibly greater than 100% due to leverage, a greater long-side tilting performance will increase the overall performance. Conversely, since the capital invested in short positions is negative, a negative short-side tilting performance is needed in order to increase the portfolio tilting performance.

[26] As their primary measure, Kacperczyk et al. (2014) sum only over the securities actually held by the fund (N_J < N_M). This is potentially misleading, because the sum of market-cap weights is below 100%, resulting in an upward biased estimate of tilting performance. Alternatively, one could rescale the market-cap weights to 100% over the set of securities N_J. That would change the interpretation, however, since the investment universe of a factor fund typically consist of the top-ranked stocks on a particular characteristic. A weight deviation would then arise only if the fund deviated from value weights within the investment universe of a particular factor strategy.

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 for HMFs (ETFs) is from 01/2006 (01/2010) to 12/2019. */**/*** 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	-0.844***	-0.425***	-0.858***	-0.243	-1.643***	-1.159***
	(8.27)	(3.96)	(5.48)	(1.47)	(5.55)	(7.61)
Nobs	4,627	1,238	443	426	102	1,282

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	-1.604***	-0.895***	-1.333***	-1.488***	-2.497***	-2.272***
	(14.08)	(8.02)	(5.57)	(7.44)	(5.99)	(14.92)
Nobs	3,384	754	277	239	75	1,174

Panel C: Low Risk Tilts for HMFs

	Low Risk (LVOL) Tilt				Total Factor tilt (Value + Mom. + CAG + Prof. + LVOL)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	-0.0543*	0.3761***	-0.3853***	-0.9026***	0.9898***	2.0550***	-0.0096	-2.9517***
	(1.68)	(5.37)	(9.60)	(12.56)	(6.09)	(8.40)	(0.08)	(12.11)
Nobs	4,839	3,172	4,627	3,384	4,839	4,839	4,627	3,384

Panel D: Low Risk ETFs

	VAL	MOM	CAG	PROF	LVOL	Total Factor Tilt (1-2)	Total Factor Tilt (1-4)	Total Factor Tilt (1-5)
	(1)	(2)	(3)	(4)	(5)			
Average	0.046	-0.008	0.303***	-0.066	1.262***	0.038	0.274	1.536***
	(0.53)	(0.17)	(4.22)	(0.55)	(9.21)	(0.51)	(1.58)	(7.42)
Nobs	263	263	263	263	263	263	263	263

Table IA-2: Factor Tilts and Fund characteristics

This table reports the results for pooled OLS regressions of fund-quarter factor tilts (value, momentum, conservative asset growth, and profitability) 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 and *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 01/2006 to 12/2019. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (*t*-statistics in brackets).

	Total Factor tilt (Value + Mom.)				Total Factor tilt (Value + Mom. + CAG + Prof.)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Gross Eq. Levg.	1.2294***	1.3829***	0.4259***	-0.5323***	2.4268***	2.8209***	0.9113***	-0.9971***
	(6.80)	(6.42)	(3.54)	(3.36)	(7.61)	(6.95)	(5.03)	(2.93)
Net Flow	0.0141*	0.0163	0.0110*	-0.0085	0.0350**	0.0334*	0.0232**	-0.0169
	(1.75)	(1.54)	(1.91)	(0.92)	(2.37)	(1.80)	(2.20)	(0.92)
Exp. Ratio.	-0.2221**	-0.1387	-0.2337***	0.1552	-0.5024**	-0.4907*	-0.6636***	0.4215
	(2.25)	(0.99)	(2.64)	(1.29)	(2.57)	(1.72)	(3.81)	(1.39)
ln(*AUM*)	-0.0761**	-0.1040*	-0.0375	0.1701***	-0.1724**	-0.2357**	-0.1276**	0.3274***
	(2.05)	(1.82)	(1.19)	(3.40)	(2.42)	(2.03)	(2.32)	(2.68)
ln(*AGE*)	0.3421***	0.4659***	0.2996***	-0.2294*	0.5832***	0.9126***	0.4593***	-0.6180**
	(3.71)	(3.47)	(3.97)	(1.96)	(3.12)	(3.04)	(3.48)	(2.15)
Turnover	0.0135	0.0179	0.0255*	0.0267	-0.0297	-0.0448	-0.0293	0.0864*
	(0.98)	(0.94)	(1.66)	(1.21)	(0.96)	(1.15)	(1.06)	(1.81)
Fixed Effects								
Calendar time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.223	0.160	0.112	0.157	0.243	0.184	0.124	0.120
Nobs	4,604	4,604	4,400	3,233	4,604	4,604	4,400	3,233

Total factor tilts (*VAL* + *MOM* + *CAG* + *PROF*) by Leverage sub-sample (*q*-1)

	Low leverage				High leverage			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.2939***	0.7165***	0.1851*	-1.2645***	1.7158***	2.7632***	0.5381***	-2.3683***
	(3.66)	(5.34)	(1.70)	(7.44)	(6.98)	(8.29)	(3.31)	(9.91)
Nobs	2,186	2,186	2,068	936	2,538	2,538	2,461	2,402

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 ($k \in [1,4]$). Panel A (B) provides the results for HMFs (ETFs) with large 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 for HMFs (ETFs) is from 01/2006 (01/2010) to 12/2019. */**/*** 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	0.928***	0.888***	0.868***	0.859***
	(48.31)	(26.92)	(22.90)	(20.17)
Adjusted R2	0.730	0.602	0.543	0.518
N	1,330	1,292	1,261	1,219

	Value tilt				Momentum tilt			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.900***	0.830***	0.781***	0.737***	0.835***	0.741***	0.690***	0.687***
	(63.04)	(35.42)	(28.65)	(21.51)	(34.84)	(20.34)	(16.84)	(16.18)
Adj. R2	0.780	0.651	0.574	0.499	0.667	0.492	0.416	0.405
N	1,330	1,292	1,261	1,219	1,330	1,292	1,261	1,219
	Conservative Asset Growth				Profitability			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.864***	0.783***	0.726***	0.688***	0.874***	0.813***	0.791***	0.784***
	(46.42)	(31.65)	(22.67)	(18.62)	(40.19)	(28.67)	(22.85)	(19.58)
Adj. R2	0.701	0.556	0.476	0.428	0.703	0.566	0.521	0.502
N	1,330	1,292	1,261	1,219	1,330	1,292	1,261	1,219

Panel B: Exchange-Traded Funds

	(1)	(2)	(3)	(4)
Total Factor tilt	0.826***	0.727***	0.651***	0.626***
	(18.05)	(10.61)	(7.73)	(6.91)
Adjusted R2	0.448	0.278	0.198	0.174
N	991	946	896	862

	Value tilt				Momentum tilt			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.959***	0.956***	0.961***	0.967***				
	(65.68)	(41.56)	(30.77)	(26.20)				
Adj. R2	0.867	0.797	0.767	0.738				
N	991	946	896	862				
	Conservative Asset Growth				Profitability			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.890***	0.828***	0.776***	0.749***	0.916***	0.896***	0.863***	0.835***
	(25.95)	(18.59)	(13.97)	(11.89)	(33.93)	(22.66)	(17.39)	(13.74)
Adj. R2	0.700	0.584	0.496	0.452	0.786	0.699	0.614	0.563
N	991	946	896	862	991	946	896	862

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 hedged mutual funds (ETFs) with a large factor tilt and a multi-factor designation in q-4. The sample period for HMFs (ETFs) is from 01/2006 (01/2010) to 12/2019. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

		Sample: HMFs				Sample: ETFs			
		Value (q-4)				Value (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**33.3%**	11.9%	3.8%	2.4%	**47.8%**	5.7%	1.2%	0.3%
	2	9.5%	**14.4%**	8.5%	2.4%	5.3%	**7.8%**	2.9%	0.8%
	3	3.9%	7.2%	**11.0%**	7.8%	1.4%	2.7%	**7.8%**	5.6%
	4	1.9%	2.6%	7.4%	**13.3%**	0.6%	0.7%	1.5%	**8.0%**
		Momentum (q-4)				Momentum (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**22.3%**	6.1%	3.5%	3.9%	**4.1%**	1.0%	0.6%	0.9%
	2	8.8%	**8.2%**	6.3%	5.0%	2.9%	**2.0%**	0.9%	1.0%
	3	6.1%	7.1%	**11.3%**	7.8%	1.2%	2.6%	**9.4%**	4.8%
	4	5.3%	6.4%	8.8%	**24.5%**	3.2%	4.2%	11.4%	**49.9%**
		Conservative Asset Growth (q-4)				Conservative Asset Growth (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**10.1%**	9.3%	5.6%	1.5%	**12.6%**	4.1%	2.0%	0.5%
	2	7.4%	**25.1%**	13.8%	4.9%	4.2%	**38.7%**	10.6%	2.4%
	3	3.6%	12.9%	**21.2%**	7.4%	0.8%	6.5%	**12.2%**	2.2%
	4	1.3%	3.6%	4.9%	**8.9%**	0.0%	0.7%	2.0%	**0.6%**
		Profitability (q-4)				Profitability (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**16.1%**	7.0%	2.9%	1.6%	**11.9%**	4.3%	2.4%	0.6%
	2	6.6%	**8.7%**	8.1%	3.7%	1.7%	**10.4%**	6.3%	2.0%
	3	3.0%	6.3%	**13.7%**	11.1%	1.3%	7.5%	**24.6%**	9.6%
	4	2.1%	4.8%	10.7%	**35.0%**	0.9%	1.2%	4.4%	**10.8%**

Table IA-5: 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 6 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 -0.5 < total factor tilt < 0.5 deciles; a *moderate* factor tilt is a portfolio with 0.5 ≤ total factor tilt < 1.5 deciles; a large factor tilt is a portfolio with a total factor tilt ≥ 1.5. 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 factor-based ETFs. The sample period for HMFs (ETFs) is from 01/2006 (01/2010) to 12/2019. */**/*** 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	-0.204***	-0.241***	-0.251***	-0.004	-0.015	-0.023	0.005	0.047
	(5.64)	(5.94)	(4.41)	(0.04)	(1.31)	(1.11)	(0.29)	(1.33)
Nobs	805	804	783	631	1,275	1,274	1,215	763
	Moderate Factor Tilt				Large Factor Tilt			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.101***	0.176***	0.095***	-0.159***	0.420***	0.619***	0.218***	-0.467***
	(6.73)	(5.28)	(5.45)	(2.73)	(17.82)	(14.34)	(11.05)	(8.99)
Nobs	918	918	868	496	1,445	1,445	1,396	1,262

	Actual (net) Returns			
	Contrary	Marginal	Moderate	Large
Average	-0.190***	-0.009	0.085***	0.436***
	(5.83)	(0.86)	(5.86)	(17.67)
Nobs	844	1,380	956	1,484

Panel B: Smart-beta ETF total factor loading

	Holdings-based return: Active/multi-factor ETFs				Holdings-based return: Single-Factor ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-0.190*	0.158***	0.272***	0.456***	-0.081	0.163***	0.320***	0.467***
	(1.76)	(4.30)	(10.15)	(20.43)	(1.51)	(4.17)	(13.93)	(20.17)
Nobs	174	284	389	539	845	1,156	1,287	887

	Net return: Active/multi-factor ETFs				Net return: Single-Factor ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-0.170	0.167***	0.271***	0.453***	-0.091*	0.165***	0.323***	0.475***
	(1.55)	(4.57)	(9.88)	(21.77)	(1.70)	(4.20)	(14.27)	(21.02)
Nobs	174	287	391	546	858	1,173	1,290	898

Table IA-6: Total Factor Tilt and Derivative Use

This table reports the results for pooled OLS regressions of fund-quarter total factor tilt on derivative use and fund characteristics at *q*-1. Derivative use (*#Deriv.*) is a dummy variable that equals 1 if the fund reports having at least one derivative position (option, future, or swap) at *q*-1, and 0 otherwise. Fund characteristics include the net expense ratio (*Exp. Ratio*), assets under management (*AUM*), fund age since inception (*AGE*), the net fund flow over the prior year (*Net Flow*), and the implied *Turnover* (defined as min($buys, $sells) divided by the average AUM over the year, as reported in CRSP MFDB). In some specifications, we also control for the *Gross Equity Leverage*, or total market value of long + short positions scaled by *AUM*. The sample period is from 01/2006 to 12/2019. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (*t*-statistics in brackets).

Y = Total Factor tilt (VAL + MOM + CAG + PROF)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Net Flow	0.037**	0.040***	0.036**	0.038**	0.035**	0.038**	0.042**
	(2.31)	(2.68)	(2.27)	(2.57)	(2.43)	(2.58)	(2.49)
Exp. Ratio.	-0.467*	-0.398*	-0.441*	-0.392*	-0.462**	-0.470**	-0.526**
	(1.95)	(1.78)	(1.86)	(1.79)	(2.49)	(2.50)	(2.50)
ln(*AUM*)	-0.191**	-0.141*	-0.168**	-0.151*	-0.154**	-0.153**	-0.146
	(2.37)	(1.73)	(2.05)	(1.81)	(2.09)	(2.03)	(1.61)
ln(*AGE*)	0.538**	0.621***	0.532***	0.607***	0.602***	0.633***	0.608***
	(2.57)	(2.98)	(2.60)	(2.93)	(3.18)	(3.34)	(2.63)
Turnover	-0.054**	-0.071***	-0.051*	-0.067***	-0.037	-0.040	-0.044
	(2.03)	(2.90)	(1.96)	(2.64)	(1.24)	(1.33)	(1.36)
#Futures > 0	-0.286					0.342**	0.487***
	(1.31)					(2.21)	(2.73)
#Options > 0		-1.409***				-0.729***	-0.899***
		(5.66)				(3.16)	(3.15)
#Swaps > 0			-0.608***			-0.054	-0.081
			(2.76)			(0.25)	(0.34)
#Deriv. > 0				-1.243***	-0.500**		
				(4.62)	(1.97)		
Gross Eq. Levg.					2.190***	2.170***	2.071***
					(6.77)	(6.67)	(6.03)
Fixed Effects							
Calendar time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.037	0.124	0.043	0.109	0.253	0.266	0.260
Nobs	4,677	4,677	4,677	4,677	4,604	4,604	3,926

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*, *moderate* and *large*) interacted with a dummy for HMFs. The omitted (benchmark) group consists of HMFs and ETFs with contrary/marginal factor tilts. Columns (1), (2), (5) and (6) include HMFs and active/multi-factor ETFs, while columns (3), (4), (7) and (8) include HMFs and all ETFs. When including all ETFs, we further split moderate and large factor tilt dummies into those with single- or multi-factor focus (based on our holdings analysis). In Panel A we repeat the results for holdings-based and actual (gross) returns with factor loadings estimated over the prior 36 months. In Panel B we present results for the KNV multi-factor picking/factor tilting performance. Finally, in Panel C, we estimate CAPM or FF6 alphas with control variables that are cross-sectionally standardized to mean zero, variance one. The first two controls, *turnover* and net fund flows (*Net Flow*) over the prior year, are interacted with a HMF dummy. The remaining controls include the expense ratio (*Exp. Ratio*), assets under management (*AUM*) and fund *age*—these three controls are standardized by cross-section separately for HMFs and ETFs. For definitions, see Table 7. Calendar time fixed effects are included in all specifications. The sample period for HMFs (ETFs) is from 01/2006 (01/2010) to 12/2019. */**/*** 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 (monthly betas in t-1 to t-36)

	Holdings-based returns			Actual (gross) returns		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Contrary tilt	0.0521	0.0365	0.0893	0.0438	0.0325	0.0762
	(1.63)	(1.08)	(1.40)	(1.22)	(0.92)	(0.94)
× HMF	-0.1396***	-0.0896	-0.2108***	-0.1530***	-0.0881	-0.2308**
	(2.99)	(1.65)	(2.65)	(2.65)	(1.35)	(2.32)
Moderate tilt	0.0839***	0.0874***	0.0719*	0.0648**	0.0658**	0.0603
	(3.19)	(2.89)	(1.84)	(2.32)	(1.98)	(1.48)
× HMF	-0.0506	-0.0536	-0.0389	-0.0448	-0.0568	-0.0283
	(1.49)	(1.09)	(0.87)	(1.11)	(0.96)	(0.53)
Large tilt	-0.0179	-0.0233	-0.0171	-0.0558*	-0.0696	-0.0519
	(0.57)	(0.45)	(0.53)	(1.72)	(1.20)	(1.53)
× HMF	0.0996***	0.0598	0.1049***	0.1074***	-0.0193	0.1181***
	(2.76)	(0.53)	(2.82)	(3.07)	(0.17)	(3.37)
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Single factor	Full	Single factor	Multi factor
Fixed effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.068	0.075	0.058	0.055	0.066	0.048
N	31,221	18,922	20,914	32,792	18,726	20,733

Panel B: Multi-factor picking and timing performance for the complete portfolios of HMFs and ETFs

	Picking performance				Tilting performance			
	Daily β		Monthly β		Daily β		Monthly β	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contrary tilt	0.0075	0.0943*	0.0105	0.1092**	0.0423	0.0845*	0.0349	0.0521
	(0.36)	(1.72)	(0.41)	(2.04)	(1.18)	(1.84)	(1.01)	(1.40)
× HMF	-0.0158	-0.1178*	-0.0252	-0.1709**	-0.0105	-0.1169**	0.0007	-0.0564
	(0.38)	(1.75)	(0.53)	(2.38)	(0.27)	(2.14)	(0.02)	(1.12)
Moderate tilt	0.0275	0.0051	0.0327*	0.0457*	0.0398	-0.0022	0.0366	-0.0344
	(1.65)	(0.26)	(1.85)	(1.94)	(1.55)	(0.08)	(1.49)	(1.15)
× HMF	-0.0477	-0.0160	-0.1029***	-0.0669**	-0.0312	0.0269	0.0179	0.0770**
	(1.59)	(0.61)	(2.91)	(2.13)	(1.07)	(1.00)	(0.62)	(2.38)
Large tilt	0.0461	-0.0231	0.0633**	-0.0080	0.0036	-0.0164	-0.0050	-0.0260
	(1.63)	(1.28)	(2.09)	(0.42)	(0.10)	(0.71)	(0.14)	(1.10)
× HMF	-0.0505	0.0622**	-0.1147	0.0344	-0.0526	0.0783***	-0.0102	0.0989***
	(0.72)	(2.36)	(1.47)	(1.36)	(0.68)	(3.54)	(0.11)	(4.10)
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Single factor	Multi factor	Single factor	Multi factor	Single factor	Multi factor	Single factor	Multi factor
Fixed effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.043	0.037	0.045	0.047	0.112	0.082	0.111	0.081
N	18,922	20,914	18,922	20,914	18,922	20,914	18,922	20,914

Panel C: Performance regression with control variables (full sample of HMFs and ETFs)

	Holdings-based returns				Actual returns - CAPM	
	CAPM	FF6	DGTW-Char	DGTW-Time	Gross	Net
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Contrary tilt	0.0075	0.0094	0.0367	0.0044	-0.0082	0.0329
	(0.21)	(0.37)	(1.44)	(0.33)	(0.21)	(0.82)
× HMF	-0.0664	-0.0515	-0.0651	-0.0027	-0.0230	-0.1113**
	(1.35)	(1.20)	(1.62)	(0.14)	(0.41)	(1.97)
Moderate tilt	0.0404	0.0137	-0.0072	-0.0026	0.0196	0.0590*
	(1.36)	(0.80)	(0.44)	(0.27)	(0.62)	(1.90)
× HMF	0.0289	-0.0152	0.0102	-0.0005	0.0598	-0.0231
	(0.82)	(0.58)	(0.40)	(0.03)	(1.45)	(0.56)
Large tilt	-0.0604*	-0.0258	-0.0242	0.0165	-0.0900**	-0.0436
	(1.67)	(1.27)	(1.35)	(1.38)	(2.31)	(1.13)
× HMF	0.1870***	0.0232	0.0692**	0.0330**	0.2109***	0.1196***
	(4.73)	(0.70)	(2.55)	(2.27)	(4.81)	(2.73)
Turnover	-0.0989***	-0.0924***	-0.0656***	-0.0206*	-0.1757***	-0.1937***
	(2.66)	(4.02)	(3.32)	(1.66)	(3.92)	(4.18)
Turnover × HMF	0.1126***	0.0947***	0.0792***	0.0191	0.1591***	0.1696***
	(2.90)	(3.51)	(3.46)	(1.40)	(3.25)	(3.37)
Net Flow	-0.0091	-0.0065	-0.0141	-0.0057	-0.0138	-0.0123
	(0.68)	(0.68)	(1.46)	(0.92)	(0.95)	(0.85)
Net Flow × HMF	-0.0288	0.0117	-0.0160	0.0032	-0.0140	-0.0102
	(1.42)	(0.75)	(1.01)	(0.32)	(0.60)	(0.44)
Exp. Ratio	0.0010	0.0120	0.0081	0.0032	0.0019	-0.0236
	(0.08)	(1.15)	(0.91)	(0.90)	(0.12)	(1.57)
ln(*AUM*)	0.0196*	-0.0086	-0.0208**	0.0041	0.0371***	0.0351**
	(1.67)	(0.98)	(2.56)	(1.08)	(2.69)	(2.56)
ln(*AGE*)	-0.0457***	0.0036	-0.0023	-0.0081*	-0.0624***	-0.0582***
	(3.32)	(0.31)	(0.27)	(1.84)	(4.18)	(3.94)
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Fixed effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.078	0.048	0.056	0.028	0.065	0.066
N	30,090	30,090	30,090	27,615	30,251	30,307

Table IA-8: Calendar Time Portfolios

This table reports the results for calendar time long-short portfolios in HMFs or ETFs with large or contrary factor tilts. Funds in each leg are equally weighted (with a minimum of five funds). The CAPM and Fama-French 6-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 12/2019.

Panel A: Holdings-based returns

	CAPM		FF6						
	α	MKT	α	MKT	SMB	HML	WML	CMA	RMW
Large HMF-Large ETF	1.78	-0.49	1.11	-0.44	-0.27	-0.05	-0.05	-0.08	-0.05
	(2.30)	(17.23)	(1.55)	(22.3)	(6.78)	(0.84)	(1.16)	(1.29)	(0.89)
Large HMF-Contra HMF	3.27	-0.04	1.74	0.02	-0.04	0.19	0.12	0.14	0.35
	(2.80)	(1.13)	(2.21)	(0.98)	(0.96)	(5.1)	(4.72)	(3.27)	(6.78)
Contra ETF-Large ETF	0.71	0.04	1.17	0.01	0.02	-0.33	-0.14	-0.16	-0.17
	(0.53)	(0.99)	(1.76)	(0.24)	(0.62)	(5.73)	(4.00)	(1.6)	(2.43)
Contra ETF-Contra HMF	2.21	0.48	1.84	0.46	0.25	-0.07	0.03	0.05	0.23
	(2.09)	(22.09)	(2.53)	(18.71)	(9.58)	(1.79)	(1.00)	(1.35)	(6.95)

Panel B: Actual (gross) returns

	CAPM		FF6						
	α	MKT	α	MKT	SMB	HML	WML	CMA	RMW
Large HMF-Large ETF	1.34	-0.54	0.42	-0.48	-0.28	-0.06	-0.02	-0.04	-0.07
	(1.76)	(16.26)	(0.67)	(19.12)	(7.61)	(1.00)	(0.40)	(0.43)	(1.10)
Large HMF-Contra HMF	2.09	-0.01	0.41	0.06	-0.04	0.23	0.16	0.14	0.36
	(1.6)	(0.22)	(0.45)	(2.57)	(1.20)	(5.73)	(6.44)	(2.48)	(5.49)
Contra ETF-Large ETF	1.04	0.04	1.37	0.01	0.03	-0.32	-0.13	-0.18	-0.14
	(0.76)	(1.11)	(2.16)	(0.50)	(0.78)	(6.07)	(3.83)	(1.87)	(2.13)
Contra ETF-Contra HMF	1.82	0.57	1.40	0.55	0.27	-0.02	0.04	-0.01	0.29
	(1.46)	(20.83)	(1.58)	(22.26)	(7.98)	(0.47)	(1.36)	(0.11)	(5.62)