Variation in the Value of Active Share Across Regions of Investments: Evidence from Global Equity Funds

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ABSTRACT

Using a worldwide sample of 3,250 global equity funds, we provide out-of-sample evidence of active share as a return predictor. However, a global fund's within-region active share predicts superior performance in Europe and Asia-Pacific, but not in the United States. We reconcile this difference by showing that highly active global managers (based in the U.S. or elsewhere) have outperformed both in U.S. and international markets primarily when they are on "right" side of equity anomalies. The weak return predictability of active share in the U.S. stems from domestic anomalies and is not generalizable to global markets.

JEL Classification: G11, G12, G14, G15, G23

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1 Introduction

There is an ongoing debate in the literature on whether the degree of active portfolio management predicts superior performance. To quantify activeness, Cremers and Petajisto (2009) introduce active share, which captures the extent to which a fund's portfolio weights deviate from those of its benchmark. They find that the most active U.S. equity mutual funds outperformed over the 1980-2003 period. Subsequent work confirms the value of active share as a return predictor in U.S. taxable bond funds (Choi, Cremers, and Riley (2023)) and in U.S. equity separate accounts (Cremers, Fulkerson, and Riley (2022)). However, other studies on U.S. equity funds cast doubt on the predictive ability of active share in unconditional tests. Frazzini, Friedman, and Pomorski (2016) and Lan, Moneta and Wermers (2023) show that active share loses its significance in tests that control for investment style, while Jones and Mo (2021) document a marked decline in return predictability since the early 2000s. Yet, active share remains a strong return predictor in domestic equity funds from around the world (Cremers, Ferreria, Matos, and Starks (2016)). How can we reconcile these differences between U.S. and international markets?

We consider this question in the unique context of active *global* equity funds, which have a mandate to invest across multiple continents, and which hold about half of their assets in U.S. equities on average. Global funds provide a unique setting to consider this question for several reasons. First, by analyzing the relation between active share and future returns in the U.S. portion of a global fund relative to other regions of the same fund, we can observe the actions of the same manager operating in different stock markets. Second, by holding constant the investment mandate and manager location, we can also rule out an alternative explanation based on differential access to global information between U.S. and non-U.S. managers (Albuquerque et al. (2009)). Third, we can rule out that the regulatory environment or investor behavior within any one country influences the results via sub-sample analysis based on a fund's country of sale. Finally, by focusing on funds with foreign portfolios (global funds only have a minimal allocation to the market in which they are sold), we can rule out a home-country advantage (e.g., Demirci, Ferreira, Matos, and Sialm (2022)).[1] Our sample includes the portfolio holdings of 3,250 global equity funds based in 19 countries over the period 2001 to 2021. These funds collectively managed $4.1 trillion in assets at the end of the sample period.

We start by showing that highly active global equity funds perform better on average. While recent studies of U.S. equity funds argue that active share only works when using the right conditioning information (e.g., Cremers et al. (2022)), we show that active share unconditionally predicts higher performance in global funds. We estimate the results separately for "true" global equity funds and global ex-U.S. equity funds (that invest worldwide except for the United States).[2] Although the return predictability is present for both sub-samples, it is markedly stronger for global ex-U.S. funds. These results imply that there are significant differences in the value of active share across regions, especially between U.S. and international equity markets. Differences in active share across countries of sale, or between global and global ex-U.S. funds, are economically small and cannot explain the observed differences in performance.

These variations in return predictability by investment mandate may instead arise because the information content of active share differs between funds. Global managers may create value by over- or under-weighting not just specific stocks, but also countries or regions, relative to the benchmark. To ensure that country selection does not contaminate our results, we remove the

[1] The sole exception is U.S.-sold global equity funds, though they are far less popular among U.S. investors relative to global ex-U.S. equity funds. We analyze ex-U.S. funds separately.
[2] The majority (>75%) of U.S.-sold funds have a "global ex-U.S. equity" mandate that exclude the U.S. equity market. The vast majority (>90%) of funds sold outside of the U.S. follow a "global equity" mandate with substantial investment in the United States. For this group, the home country allocation is, on average, less than 7.5%.

influence of active country picks from the calculation of active share, and find virtually identical results. Hence, the return predictability of active share primarily comes from identifying managers that successfully engage in "stock picking" within countries, and is therefore unlikely to capture a dimension of activeness that is unique to global portfolios.

To better address why the value of active share differs between U.S. and international markets, we decompose each global fund's portfolio into three regional sub-portfolios (United States, Europe, and Asia-Pacific). We find that the region-specific active share—i.e., how active a fund is within a region compared to the benchmark's holdings in the same region—predicts significantly higher returns in Europe and Asia-Pacific, but weakly lower returns for the U.S. sub-portfolio. To illustrate, the top quintile on regional active share outperforms the bottom quintile on FFC4 alpha by as much as 1.44% per year in Asia-Pacific, 1.29% in Europe, and -0.24% in the United States. These differences are large enough to explain the stronger fund-level performance of global ex-U.S. equity funds relative to truly global equity funds. In general, our results confirm that managers within-region activeness matters for subsequent performance, and that they find value across the globe—just not in the United States.

The traditional approach to amplifying the return predictability of active share in U.S. equity funds is to condition it on the manager's investment horizon (Cremers and Pareek (2016)), or prior performance (Cremers et al. (2022)). However, conditioning on these two variables actually magnifies the gap in return predictability in global funds' investments in Europe and Asia-Pacific vis-à-vis the United States, leaving the puzzle unsolved.

Our results suggest that the predictive ability of active share is lower in U.S. equity markets even though global managers are as active in the U.S. as they are in international markets. We explain this puzzle by drawing on a recent literature on active managers and asset pricing anomalies (e.g., Avramov, Cheng, and Hameed (2020), Irvine, Kim, and Ren (2022)). Avramov et al. (2020) show that the return predictability of activeness in U.S. equity mutual funds depends in part on being on the "right" side of mispricing (i.e., by tilting towards rather than against anomalies). Following Avramov et al. (2020), we construct an anomaly tilt measure that captures the extent to which a fund is betting on a composite index of eight distinct anomalies (Stambaugh, Yu, and Yuan (2012)). Specifically, we compute the portfolio-weighted average characteristic (or decile) score of the stocks held in excess of the corresponding value-weighted score of the benchmark index fund, and then averaged across the eight anomalies.

We find evidence supporting a connection between anomaly trading, active share, and global equity fund performance. First, higher U.S. active share is associated with lower U.S. anomaly tilts, while the opposite is true for Asia-Pacific, and in Europe the relationship is insignificant. Second, we find that regional sub-portfolios with high active share and high anomaly tilts outperform their low/low counterparts across all three regions. To illustrate, the difference in FFC4 alphas between the two corner portfolios is 0.91% per year for the U.S. sub-portfolio, 1.88% for Europe and 2.46% for Asia-Pacific. Overall, both results suggest that the relatively poor unconditional performance of U.S. active share in global funds connects to the returns on anomalies in U.S. stock markets.

Finally, we confirm the importance of conditioning on anomaly tilts for the whole fund when evaluating activeness. The outperformance of highly active global funds with large anomaly tilts is not only stronger by a factor of two-to-three relative to using active share alone, but the results for global vs. global ex-U.S. funds are now comparable as well. Thus, conditioning active share on anomaly tilts can fully reconcile the puzzling weakness of active share in portfolios dominated by U.S. stocks. Furthermore, the results are similar regardless of the funds' region of sale (equivalent to manager location), which helps to rule out the superiority of U.S.-based managers due to differential access to global information (Albuquerque et al. (2009)).

Our results also connect to several strands of the literature on competition, arbitrage opportunities, information disclosure, and anomalies. Both Wahal and Wang (2011) and Hoberg, Kumar, and Prabhala (2018) show that the performance of U.S. equity fund declines with the number of competitors investing in similar styles. Cremers et al. (2016) show that the active share of equity funds is higher and predicts greater performance in countries with more competition from passive funds. Our results on the superior performance of highly active funds that bet on anomalies are not materially different between U.S.-sold funds—facing the highest degree of competition from passive funds (Broman and Lovelace (2024))—and non-U.S.-sold funds.

Variation in the value of activeness over time may also be related to time-varying arbitrage opportunities within domestic markets. von Reibnitz (2017) shows that the most active funds obtain higher returns when cross-sectional alpha dispersion is higher and Jones and Mo (2021) link the weaker out-of-sample return predictability of mutual fund measures primarily to time-varying arbitrage activity. Avramov et al. (2020) document that the performance gap between funds betting on versus against anomalies widens during high sentiment periods, also suggesting time variation in arbitrage trading. Our results suggest that active managers can deliver superior performance even in the U.S. as long as they are on the right side of anomalies, making it unlikely that time variation in opportunities explains the weak performance of activeness in the U.S.

Differences in information availability and disclosure requirements across countries may also relate to variation in the value of activeness. Lantushenko and Nelling (2021) argue that the return predictability of active share during the Cremers and Petajisto sample period stems partly from the selective disclosure of information, which was curtailed by regulation FD in the United

States (before our sample period). A similar regulation, the European Union Market Abuse Directive, was implemented in the EU in 2007 (Cowan and Salotti (2020)). Our European sub-portfolio results are, however, not materially different pre- or post-2008, which suggests that differences in information disclosure are unlikely to be a key channel for our results. The fact that global funds (which have a mandate to invest primarily in foreign markets) seem to perform so well across many different markets suggests that variation in country- and region-specific information disclosure policy does not explain variation in activeness.

Finally, our results connect to a recent literature on whether mutual fund managers can successfully execute anomaly-based trading strategies. The unconditional results in Avramov et al. (2020) show that the return predictability of anomaly tilts primarily stems from funds that bet against anomalies and consequently underperform. Patton and Weller (2020) show that long-only U.S. equity funds cannot achieve the on-paper performance of the value and momentum factors, while Broman and Moneta (2024) show that long-short mutual funds can successfully trade on several well-known anomalies, especially on the short side, while factor-based ETFs cannot. By contrast, we show that global funds that are highly active and that bet on anomalies outperform, especially outside of the United States.

2 Data and Variable Definitions

We collect data on mutual fund returns and characteristics from Morningstar Direct and the CRSP Mutual Fund Database (henceforth CRSP MFDB; only for U.S.-sold funds). Morningstar Direct contains both live and dead funds and is free of survivorship bias (e.g., Betermier, Schumacher, and Shahrad (2023)). Portfolio holdings come from Morningstar because it provides reliable and complete holdings on a quarterly basis throughout our sample period. Underlying stock returns and characteristics are from CRSP (U.S. firms), Compustat/North America (Canadian firms) and

Compustat/Global (non-U.S. firms). Below, we summarize the main data filters used. Additional details can be found in Appendix 1.

Our analysis focuses on open-end equity mutual funds with a global or international investment mandate that are sold throughout the world, as identified by Morningstar Direct. In the mutual fund industry, "international" or "global ex-U.S." refers to funds that invest across stock markets outside of the U.S. (sold almost exclusively in the U.S. or Canada), whereas "global" or "world" refers to funds that invest worldwide including the U.S. (sold throughout the world). We select these funds based on the Morningstar Category variable. For the purposes of our study, we refer to all of these funds as "global funds" and when necessary, distinguish those that cannot invest in the United States as "global ex-US funds".

We include funds domiciled in countries with developed mutual fund markets to ensure high data quality and good coverage. In contrast to a few recent international mutual fund studies (e.g., Ferreira et al (2012) and Keswani, Medhat, Miguel, and Ramos (2020)), we also include offshore funds from Luxembourg and Ireland since they use the same regulatory structure as most other European funds, known as the Undertakings for Collective Investments in Transferable Securities, or UCITS (see Khorana, Servaes, and Tufano (2005, 2009)). Luxembourg and Ireland are the two largest fund domiciles in the world after the U.S. based on total AUM (ICI (2022)).

Similar to prior work (e.g., Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014)), we include a fund in our sample only after it passes \$10 million in AUM (U.S.-dollar denominated). Further, we exclude observations for funds that have less than 70% of their assets in equities in the prior year (as in Amihud and Goyenko (2013)), or less than 50% in common stock (to filter out funds-on-funds not captured by the static indicators), as well as funds that have short positions of more than 10% on average. Furthermore, funds must have at least two years of holdings data (as in Jiang, Yao, and Yu (2007)) and to report holdings on a quarterly basis to ensure comparability across countries.

Our regression sample is from January 2001 to December 2021, although individual countries enter the sample only after coverage is established and holdings data is widely available. The first country to enter our sample is the United States (2001) followed by Canada (2003), most of Europe (2004-2006) and Australia (2005). In terms of basic fund characteristics (e.g., returns and AUM), the coverage for most countries is well established by 2002.

2.1 Performance Measures

We assess gross fund performance using a factor-based risk adjustment, as well as a benchmark-based adjustment. For the factor-based approach, we include the Capital Asset Pricing Model (*CAPM*), the four-factor Fama-French-Carhart (*FFC4*) and the six-factor Fama-French (*FF6*). In all cases, we use a rolling 36-month window to estimate the factor loadings.

To construct appropriate factors for our global funds, we use AQR's country factors for the CAPM and FFC4 and weight each country by each fund's portfolio weight to that country in the prior quarter (t-1).[3] For the FF6, we instead use regional factors from Fama French's data library and compute region-weighted factors, weighting each region by the fund's regional weight in t-1.[4] This methodology is based on Broman, Densmore and Shum-Nolan (2023), and it is consistent with Fama and French (2012, 2017) and Hollstein (2022), who show that local factors are superior to global factors that weigh each country by its lagged market capitalization. We emphasize these bespoke, fund-specific, factors to avoid misattributing performance from

[3] AQR's risk factors are available only for developed markets. For emerging markets, we use the corresponding regional factors. The median allocation in emerging markets is relatively low, however, at around 5%.

[4] Our results are nearly identical, or even stronger, when using Fama-French regional factors for all three factor models. Similar results are also obtained with market-capitalization weighted global factors. These results are unreported for conciseness.

persistent country (or region) tilts that are likely driven by investor preferences or differences in investment mandates. As a case in point, global equity funds domiciled in Europe have historically underweighted the U.S. stocks by 5.5% (relative to benchmark weight of 55.5%) and overweighted European stocks by 8.6% (benchmark weight of 28.5%).

For the benchmark approach, we evaluate fund performance relative to a set of style benchmarks, since the average retail investor has been shown to rely on them to indirectly adjust for risk instead of a multi-factor model (Chakraborty, Kumar, Muhlhofer, and Sastry (2020), Evans and Sun (2021)). Moreover, fund managers are often evaluated against style benchmarks (Evans, Gómez, Ma, and Tang (2023)), which gives them an incentive to maximize this measure. We define the *benchmark-adjusted alpha* as the alpha of the fund's gross return relative to the style benchmark return, where the beta with respect to the style benchmark is estimated using the prior 36 months of data. To select the style benchmark for each fund, we classify each fund based on its geographical investment mandate (global vs. global ex-U.S.), stock market development status (developed only vs. developed and emerging), size (large-, or mid-/small-cap) and style tilt (value, blend or growth). We then choose the corresponding MSCI benchmark index for each fund (see Internet Appendix IA-1 for additional details).[5] An important difference between factor- and benchmark-adjusted performance is that the latter uses market-capitalization weights for each country, while the former uses the fund's actual allocation to that country.

2.2 Return Predictors

Our main return predictor is active share (Cremers and Petajisto (2009)). In later analysis, we use conditioning variables, primarily anomaly tilt (Avramov et al. (2020)), but also holding horizon

[5] Another commonly used approach is to benchmark mutual funds relative to their style peers (Evans et al. (2023)). We obtain comparable results if we replace the gross style benchmark return by the equal-weighted return of the mutual fund's style peers that are available for sale in the same country.

(e.g., Lan, Moneta and Wermers (2023)) and past performance (Cremers et al. (2022)). We briefly summarize each predictor and provide additional details in Appendix 2.

Active share is based on deviations of a fund's actual portfolio weights from those of its benchmark (Cremers and Petajisto (2009)). Following Doshi, Elkamhi, and Simutin (2015) and Cremers et al. (2016), we use broad-based market-cap weighted benchmarks (*active share broad-based*) to calculate active share. Specifically, for global ex-U.S. equity funds we use the Vanguard Total International Stock Index Fund (that includes developed and emerging markets) and the Vanguard Developed Markets Index Fund (that excludes emerging markets). For global equity funds, we use the Vanguard Total World Stock Index Fund. Vanguard index funds are widely used by mutual fund researchers for benchmarking purposes (see, e.g., Berk and van Binsbergen (2015)).

Since the Vanguard funds that serve as our benchmarks have no style tilt, we include style fixed effects in the analysis to better account for the influence of style. For robustness, we also present results for an alternative measure of active share where the benchmark index is replaced by the aggregate portfolio of active funds with the same size (large or mid/small-cap) and style tilt (only for large-cap funds), and sold in the same region (*active share style peers*). This measure is similar to the portfolio measure by Wahal and Wang (2011) and Sias, Turtle, and Zykaj (2016). Another important feature of this measure is that it is region neutral, since the active share of each fund is only computed relative to other funds sold in the same region.

Anomaly tilts measure the extent to which a portfolio is tilted towards eight well-known asset pricing anomalies from Stambaugh et al. (2012). We compute for each stock the characteristic (decile) scores on a particular anomaly (e.g., momentum). Following Avramov et al. (2020), we compute fund-level anomaly tilts as the portfolio-weighted average characteristic score of the stocks held by the fund in excess of the corresponding value-weighted score of the benchmark index fund, and then averaged across the eight anomalies. We sign the measure such that higher numbers indicate greater anomaly tilts, and greater expected returns.

To capture a fund's holding horizon, we use a holdings-based proxy of fund turnover called the *churn ratio*. It is computed as the dollar value of quarterly trades of securities scaled by the total market value of the portfolio, averaged over the prior four quarters (e.g., Gaspar, Massa, and Matos (2005) and Wang, Zhang, and Zhang (2020)).[6]

2.3 Descriptive Statistics

In Table 1, Panel A, we report snapshots of the total number of funds and AUM by country of sale in an early, middle, and final year of the sample. As the name suggests, the country of sale refers to the country in which the fund is available for sale. Most funds are only sold in one country; cross border refers to funds that are available for sale in multiple countries in Europe and/or globally.

[Table 1]

At the end of the sample period in December 2021, we have a total of 1,984 funds managing more than $3.2 trillion in capital. U.S.-sold funds are the dominant group in terms of AUM ($1.87 trillion) with European cross-border funds a distant second ($412 billion). When measured by the number of funds, the distribution is more even with U.S. in the lead (558 funds), followed closely by cross-border funds (344), Canada (231), and the U.K. (198). For non-U.S.-sold funds, most countries are included in the sample already by 2005, although the total number of funds at that time is only 802 (out of which 335 are U.S.-sold). All countries are well represented in the middle

[6] We obtain comparable results (unreported for conciseness) if we instead use the holding duration measure by Cremers and Pareek (2016).

of the sample period in 2012, and U.S.-sold funds constitute less than a third of the total number of funds (491 out of 1568).

[Table 1]

In Panel B, we can see that global equity is the dominant fund type in Australia and Europe (>94% of the sample), whereas global ex-U.S. equity funds are more common in the U.S. (74.5%) and Canada (31.9%). Figure 1 shows the growth in the number of funds and total AUM over time by region of sale. In Panel A, we can see that the global equity fund sample grows from around 70 in 2001 (only U.S.-sold) to more than 200 in 2004 when non-U.S. funds enter the sample, then tripling to more than 600 by 2008, and steadily growing until hitting a peak of around 1,500 by 2020. By contrast, the global ex-U.S. sample size is more stable over time, ranging from 250 in 2001 to 500 in 2015, which is largely explained by the dominance of U.S.-sold funds and the maturity of U.S. market in the early 2000s.

[Figure 1]

Table 2, Panel A, provides summary statistics for the return predictors used in this study, as well as for a standard list of control variables (e.g., Ferreira, Keswani, Miguel, and Ramos (2013)). We control for fund age (*AGE*), assets under management (*AUM*) and fund family AUM (*family AUM*) to account for decreasing returns-to-scale and the resources available to fund managers; the net expense ratio (*%Exp. Ratio*) since skilled managers should generate better gross performance but capture rents by charging higher expenses (Berk and Green (2004)); net fund flows (*%Net Flow*) because flow-induced trading may adversely affect fund performance (Khan, Kogan, and Serafeim (2012), Lou (2012)); and the standard deviation of the benchmark-adjusted return since many mutual fund managers are subject to a tracking error constraint (*%Track. Err.*).[7]

[7] We use Morningstar's Branding ID variable to identify fund families and to compute family AUM. In general, the expense ratio includes not only the management fees, but also all other ongoing expenses (e.g., administration, auditing). We use Morningstar's representative cost variable to obtain comparable fee structures across countries.

[Table 2]

Active share relative to broad benchmarks is 85.63% (88.73%) on average (at the median). The corresponding numbers for the active share relative to style peers are similar at 83.10% and 85.32%, respectively. The variable *anomaly tilt* is defined as the average (decile) score across nine different anomalies. The median (25^{th} percentile) [75^{th} percentile] anomaly tilt is 0.09 (-0.09) [0.25] deciles. To better gauge the magnitude of the total anomaly tilt, the interquartile range is 0.34 deciles for each of the nine anomalies. As for measures of fund holding horizon, the average (median) churn ratio is 34.19% (27.41%) per quarter, which indicates that the average fund turns over more than one third of its positions per quarter.

Finally, we analyze the control variables. The size-based control variables (AUM and family AUM) exhibit large variations and positive skewness. In particular, while the average AUM is $0.84 billion, the median is only $0.17 billion. These variations are larger relative to prior studies that focus on U.S. equity funds, since U.S.-sold funds in our sample are substantially larger than their non-U.S. counterparts. There are also large variations in expense ratios (mean of 1.37% and standard deviation of 0.60%), which is related to the degree of competition in different markets (see e.g., Cremers et al. (2016)). Annual fund flows are similarly highly volatile (33.27%) and positively skewed (mean of 4.70% vs median of -1.64%), which is not surprising given the rapid growth in the global equity fund market outside of the United States.

Panel B summarizes the distribution (25^{th}, 50^{th}, and 75^{th} percentile) of active share measures and anomaly tilts by country of sale. Both versions of active share are within five percentage points of the full sample median for virtually every country. U.S.-sold global funds are, if anything, less active compared to funds from other countries. For all three measures of activeness, we observe that the interquartile range is several times greater *within* than across countries.

3 Active Share and Return Predictability in a Global Fund Context

Given the weak performance of active share as a return predictor in U.S. equity funds after controlling for investment style (e.g., Frazzini et al. (2016), Lan et al. (2023)), especially post publication (Jones and Mo (2021)), we start by providing additional out-of-sample evidence in the context of global funds. Our sample consists of two distinct types of funds, namely global ex-U.S. equity funds (sold primarily in the U.S. and to a lesser extent in Canada, see Table 1, Panel B), and global equity funds (sold throughout the world). We start with fund-level tests that separate the two investment mandates.

We estimate pooled OLS regressions of risk-adjusted fund performance on active share (*AS*) with controls and fixed effects, separately for global and global ex-U.S. equity funds:[8]

$$Perf_{i,t} = b_1 AS_{i,t-1} + c_1 Controls_{i,t-1} + \varphi_t + \varphi_{s,t-1} + \varepsilon_{i,t} \tag{1}$$

We use quintile dummies for active share (omitting the lowest quintile).[9] All specifications include time (φ_t) and style ($\varphi_{s,t-1}$) fixed effects to account for differences in risk-adjusted performance due to time trends (e.g., changes in competition) or style (e.g., large- vs. small-cap). Morningstar designates global equity funds into four styles—large value, large blend, large growth and small/mid-cap. Controlling for style is especially important since prior studies find that active share loses its predictive power when funds are ranked *within* style categories. Table 3 provides the results.

[8] Although Fama-MacBeth regressions are commonly employed in the literature, we focus on pooled OLS regressions because the sample size is unevenly distributed over time with fewer than 200 funds in 2001 and almost 10 times as many in 2021 (see Figure 1 and the discussion in Section 2.3). Since Fama-MacBeth equally weights every time period regardless of the number of funds in the cross section, the coefficient estimates in early time periods may be estimated with substantial noise. By contrast, pooled OLS overweights later time periods when the sample size is abundant. If the value of active share as a return predictor has diminished over time, then our pooled OLS results are not only more conservative, but also more representative going forward.

[9] Given the distinct investment mandates of the two sub-samples, we estimate quintiles separately for global and global ex-U.S. funds in each cross-section. We obtain similar results if we instead use a continuous measure of active share based on the percentile rank (ranging from 0 to 1).

[Table 3]

The results for active share relative to broad benchmarks (Panel A) strongly support the notion that active share predicts higher risk-adjusted fund performance. The magnitudes are, however, substantially stronger for global ex-U.S. equity funds. For example, the most active funds (Q5) outperform the least active ones (Q1) by 13.7 bps per month in global ex-U.S. equity funds, but by only 6.49 bps in global equity funds using the FFC4. More conservative factor models, like the FF6, are rarely used in mutual fund research. When such models are used, they often explain the bulk of the outperformance of active managers (e.g., Cremers and Pareek (2016)). Nevertheless, the Q5-Q1 difference remains as high as 12.5 bps and 6.4 bps for global ex-U.S. and global equity funds, respectively. Overall, the Q5-Q1 spread is 2-2.5 times greater for ex-U.S. funds for both factor- and style-adjusted performance measures.

So far, we have presented results for active share measured relative to broad-based market-cap weighted benchmarks (e.g., as in Doshi et al. (2015)). Style tilts may matter, though style fixed effects should absorb the average impact on active share. Nevertheless, we repeat the tests for active share relative to style peers (of other active funds sold in the same region) in Panel B and without style fixed effects. In this case, we find mostly insignificant evidence of return predictability for global equity funds, while the results for global ex-US funds remain significant (or even stronger) than before. Thus, active share is, at best, a weak return predictor for global equity funds, while the converse is true global ex-U.S. funds.

Since the vast majority of global ex-U.S. equity funds are based in North America, the split on global and global ex-U.S. is implicitly also a split by region of sale. Albuquerque, Bauer, and Schneider (2009) argue that U.S.-based institutional investors have superior access to "global" private information that is relevant for trading in many foreign countries simultaneously. Thus, the returns to active management could be inherently greater in equity funds based in North America that employ “better” managers. To address this alternative explanation, we re-estimate the results for global equity funds by region of sale. Regardless of risk adjustment, the return predictability of active share is mostly insignificant for North American sold funds; while it is stronger for European and Australian sold funds, though not strong enough to reconcile the weakness of AS in global equity funds (see Table IA-1 in the Internet Appendix). In the next section, we provide more conclusive tests by examining return predictability not only by region of sale, but also by region of investment.

A potential caveat with these results is that the information content of active share in the context of global portfolios may be different from that of active share in domestic funds (the focus of prior studies). Specifically, global fund managers may also add value by over- or underweighting specific countries or regions in order to take advantage of prevailing market conditions. To ensure that the return predictability of (global) active share comes from well-established sources of activeness (“stock picking”), we perform two tests.

First, we simply eliminate a fund’s active regional bets from the active share calculation. To achieve this, we calculate active share separately for each fund and by region of investment (U.S., Europe and Asia-Pacific) with weights summing to 100% by region, then we compute a dollar-weighted average active share across the three regions. The original and the region-weighted active share are very highly correlated (above 0.97). In unreported results, not surprisingly, we find that the return predictability of the region-weighted active share is nearly identical to that for the original measure.

Second, rather than adjusting active share itself, we instead use a measure of fund performance that captures the returns to market timing. Specifically, we use the characteristic (or style) timing measure of Daniel, Grindblatt, Titman, and Wermers (1997), which we extend to international markets following Dyakov, Jiang, and Verbeek (2020) and Broman, Densmore and Shum (2023). We find no consistent evidence of market timing by either subset of funds (see Table IA-2 in the Internet Appendix), which suggests that funds with high active share do not simultaneously engage in market timing strategies.

3.1 The Return Predictability of Active Share in Regional Sub-Portfolios

The existing literature mostly agrees that the return predictability of active share is weak for U.S. equity funds after controlling for style (Frazzini et al. (2016), Lan et al. (2023)). Since global equity funds invest about half of their portfolio in U.S. equities, it is possible that the weakness of active share in global equity is a manifestation of the weaker return predictability of measures of active management in U.S. portfolios. In this section, we focus on the regional sub-portfolio of mutual funds to assess where the return predictability is coming from.

To analyze the strength of active share as a return predictor across regions, we separate the fund-level portfolio into three mutually exclusive regional sub-portfolios: United States, Europe (including the Middle East) and Asia-Pacific.[10] While this is a coarse separation, most global funds only invest in a handful of stocks in countries with small stock markets, and many countries are dominated by firms from a handful of sectors (e.g., the market-cap industry weights are 42% for Healthcare in Denmark, 29% for Energy in Norway, and 27% for Financial Services in Italy). A finer decomposition by country is therefore not feasible.

For the regional sub-portfolios, we treat each fund's sub-portfolio as the unit of observation. We reweight the sub-portfolio weights to add to 100% by region, and use only the

[10] We discard Canadian stock holdings because the Vanguard index funds were benchmarked against MSCI's EAFE stock market index for much of the sample period, and EAFE excludes Canadian stocks. Moreover, many actively managed funds in our sample continue to be benchmarked against the EAFE index even in more recent years. Finally, Canadian holdings represent a relatively small component of most of the funds in our sample. Other regions (Latin America and Tax Havens) are not included in the analysis.

benchmark's stocks from the same region to estimate regional active share.[11] Effectively, each fund is treated as three separate portfolios. Similarly, we recompute the risk factors by only including the countries in the same region being considered.

We re-estimate Eq. (1) for each of the three regional sub-portfolios using the same fund-level control variables and fixed effects as before. We initially pool together global and global ex-U.S. funds, and we control for any unconditional differences in performance via an investment mandate fixed effect. The results in Table 4 are stark: active share has no predictive power in the U.S. sub-portfolio for any performance measure, but it is a strong return predictor in Europe and Asia-Pacific. To illustrate, for FFC4 alpha, the Q5-Q1 difference on active share is -2.0 bps per month in the U.S. sub-portfolio (insignificant), but 10.7 bps in Europe and 12.0 bps in Asia-Pacific (significant at the 1% level). Thus, the return predictability of active share is strong outside of the United States, but non-existent (or even negative) in U.S. sub-portfolios.

[Table 4]

The interpretation of the quintile dummies is similar, regardless of sub-portfolio, because the level of regional active share varies only modestly across regions (more formal tests are provided in Section 5.2). Another way to see this is to note that when fund-level active share is high (top tercile), 93%, 81%, and 82% of U.S., Europe and Asia-Pacific regional active share classifications are also high. Thus, most active funds are active in all three regions simultaneously.

A potential caveat with the results for the Europe and Asia-Pacific sub-portfolios is that they may partly reflect the superior performance of active global ex-U.S. funds (as shown in Table 3). To address this, we re-estimate the results for global equity funds only and continue to find very similar results (see Table IA-3 in the Internet Appendix). We also test whether the region of

[11] To ensure that we only include economically meaningful sub-portfolios, we require that each sub-portfolio accounts for at least 10% of the fund's total assets under management.

sale matters via sub-sample analysis. In line with our prior findings, the weakness of active share in global equity funds, and in U.S. sub-portfolios in particular, is not explained by clientele (or manager) location. It also casts further doubt on the idea that U.S.-based managers have superior access to global information (e.g., Albuquerque et al. (2009)).

4 Reconciling the Weakness of Active Share in Global Equity Funds

Recent studies argue that we need to use conditioning information to fully reveal the value of active share as a return predictor. Intuitively, managers need to deviate from the benchmark in order to generate alpha, but deviating from the benchmark does not, by itself, require skill. In the rational equilibrium model of Buffa and Javadekar (2022), unskilled managers have an incentive to increase active share and pretend to be skilled in order to attract new capital, but instead increase the volatility of active returns (tracking error) to hinder investor learning

To reconcile the puzzling weakness of active share in global equity funds with U.S. exposure, we draw on a recent study that connects active share with anomaly-based trading strategies. Avramov et al. (2020) show that the value of activeness in U.S. equity mutual funds is in part dependent on how active a fund is, the degree to which a fund actively bets against anomalies, and the dispersion of mispricing in the market. Active funds on the wrong side of anomalies underperform substantially, while active funds on the right side slightly outperform. Relatedly, several asset pricing papers argue that anomaly-based trading strategies perform poorly in U.S. equity markets (Patton and Weller (2019), Briere, Lehalle, Nefedova, and Amine (2019), Chen and Velikov (2021)), yet are profitable in international equity markets (Lu, Stambaugh and Yuan, (2017), Jacobs and Müller (2020), Baltussen et al. (2021)). Thus, if anomaly-based trading strategies perform better internationally than in the U.S., and if such strategies also require high active share, then the information content of active share (as a return predictor) will be different in the U.S. vs. internationally based on a fund's tendency to trade on anomalies. In Section 5.1, we therefore consider an interaction between active share and anomaly tilts to see if it helps to account for the difference in return predictability between U.S. and non-U.S. portfolios, and ultimately between global and global ex-US equity funds.

4.1 Active Share and Anomaly Tilts: Regional Sub-portfolios

Our primary explanation for the weakness of active share in U.S. stocks is that the information content of high active share strategies differs by region based on the extent to which a fund is betting on, or against, anomalies. In Table 5, we present sub-portfolio results where regional active share is interacted with the regional anomaly tilt. We switch from quintiles to terciles to preserve sample size and power in each group.

[Table 5]

For the first time, we see strong and consistent evidence across all regions: high active share and high anomaly tilt strategies outperform their low-low counterparts even in the U.S. sub-portfolio (Table 5). The outperformance ranges from 7.0 (FF6) to 11.4 (CAPM) bps per month for the U.S. sub-portfolio of global equity funds (column (1)), from 13.1 to 22.3 bps per month for the Europe portfolio (column (2)), and 18.3-21.7 bps for Asia-Pacific (column (4)). Although the return predictability remains stronger in non-U.S. sub-portfolios, it is far less pronounced than before. These variations in profitability are consistent with fewer opportunities to trade on anomalies in the U.S. relative to other countries, possibly due to greater arbitrage capital and/or competition (as suggested by Jacobs and Müller (2020)).

In some specifications, we even see that high active share funds with *low* anomaly tilts underperform, especially for US portfolios. It is therefore possible that the higher active share of many funds in their U.S. sub-portfolios is of the "wrong" type (i.e., betting against anomalies).

Whatever the reason for this, it is not at odds with the existing literature. For example, Edelen, Ince, and Kadlac (2016) report that U.S. institutional investors in aggregate trade contrary to anomalies in the period prior to the realization of anomaly returns. In the context of mutual funds, prior research has shown that fund managers seeking to beat their benchmark often trade against the low-vol anomaly by buying high-beta stocks (Christoffersen and Simutin (2017), Buffa, Vayanos, and Woolley (2022), Cui, Kolokolova, and Wang (2024).

In addition, the gap in return predictability between global and global ex-U.S. funds is no longer evident: all results for ex-U.S. funds are within 1 bp (columns (3) and (5)) of to the corresponding estimates for global funds. The outperformance of highly active funds that bet on anomalies is also consistent across regions of sale, suggesting that differences in clientele or manager location do not seem to matter either (as shown in Table IA-4 in the Internet Appendix). These results are also broadly similar for active share relative to style peers (Table IA-5 in the IA).

Finally, we examine the return predictability of active share interacted with anomaly tilts at the fund level (Table 6). Overall, we find strong and consistent evidence that portfolios with high active share and high anomaly tilt outperform relative to those with low active share and low anomaly tilts. Conditioning active share on anomaly tilts also strengthens the return predictability, relative to unconditional sorts on active share, despite the coarser groupings used (terciles in Tables 6 vs. quintiles in Tables 3 and 5). Importantly, the outperformance is very similar for both global and global ex-U.S. equity funds, regardless of performance measure, or sub-sample by region of sale (see Table IA-6 in the Internet Appendix). These results also remain robust to using the style peer-based measure of active share (Table IA-7 in the IA). Thus, the seemingly puzzling sub-sample results by investment mandate are not so puzzling after all as long as active share and anomaly tilts are considered jointly.

[Table 6]

4.2 The Relation between Active Share and Anomaly Tilts

To shed more light on *why* high active share alone is not sufficient in global equity funds, we consider the relationship between active share relates and anomaly tilts.

In Table 7, Panel A, we model regional active share as a function of regional anomaly tilts (with separate coefficients by regional sub-portfolio), regional sub-portfolio dummies, and fund characteristics (all lagged), as well as style and time fixed effects. All explanatory variables, other than dummies, are standardized to mean zero, variance one. Control variables enter with the expected sign: regional active share is higher for smaller funds, more expensive funds, funds with higher net flows in the prior year and funds with higher tracking error. Interestingly, the level of active share is systematically lower for U.S. portfolios (-1.9%) and higher for Asia-Pacific (by 3.9%), relative to the omitted group (Europe). This is indicative of managers being more active in regions with more alpha opportunities. This result holds universally and is therefore inconsistent with a home field advantage. That is, North American sold funds are just as likely to have a lower active share in US portfolios than European sold funds, while both have significantly higher active share in the Asia-Pacific portfolio. The latter holds for both global and global ex-U.S. funds.

[Table 7]

More importantly, the relationship between active share and anomaly tilts is highly negative for the U.S. sub-portfolio, while it is insignificant for the Europe portfolio and significantly positive for the Asia-Pacific portfolio. These results are also consistent across sub-samples by region of sale (column (2) vs. (3) and (4)), and for global vs. global ex-U.S. equity funds (column (2) vs. (1)). Similarly, U.S. (European) [Asia-Pacific] anomaly tilts are negatively (insignificantly) [positively] related to fund-level active share (see Panel B).[12]

In summary, high active share strategies in the U.S. tend to have lower anomaly tilts, which is expected to be associated with worse performance. This could explain why high active share in the U.S. sub-portfolio does not, by itself, predict better performance. Similarly, the strong return predictability of active share in Asia-Pacific may, in part, be related to the fact that high active share strategies in Asia-Pacific tend to have high anomaly tilts.

4.3 Robustness: Active Share Interacted with Holding Period or Prior Performance

In this section, we assess whether other conditioning variables can help to reconcile the weakness of active share in global equity funds, and in the U.S. portfolios of such funds. Prior research suggests that the return predictability of active share is amplified when it is interacted with measures of the fund manager's holding horizon (Cremers and Pareek (2016)) or past performance as a proxy for managerial skill (Cremers et al. (2021)). That said, more recent evidence suggests that the return predictability of active share interacted with holding horizon loses its significance when controlling for style benchmarks (Lan et al. (2023)). To assess the importance of each conditioning variable, we include interaction terms with active share first at the fund level, and then at the regional sub-portfolio level.

When fund-level performance is conditioned on active share and holding horizon, the differences between global and global ex-U.S. largely disappear, though the point estimates are noticeably weaker compared to the anomaly tilt interactions (see Panel A of Table 8). While the return predictability is far stronger when conditioning active share on prior performance (Panel B), the differences between global and global ex-U.S. equity funds remain meaningful. With FFC4

[12] The results are comparable if we instead compute active share relative to style peers (see Table IA-8).

alphas, highly active funds with good prior performance outperform by as much as 12.0 and 20.1 bps per month for global and global ex-U.S. equity funds, respectively. At first glance, these results seem to be consistent with the prior literature on U.S. equity funds and the weakness of active share in unconditional tests. However, conditioning on these two variables actually amplifies the return predictability in global funds' investments in Europe and Asia-Pacific, but not in the United States (shown next).

[Table 8]

In Table 9, we interact active share with holding horizon and prior performance at the regional sub-portfolio level. For the interaction with high holding horizon, we find significant evidence of return predictability only for non-U.S. portfolios. The results for U.S. portfolios are consistently insignificant, however. The same non-result is present for the interaction with prior performance as well. Moreover, when we estimate the regional sub-portfolio results separately for global vs. global ex-U.S. equity funds, we continue to find inconsistent results, especially for active share interacted with holding horizon (unreported for conciseness). Thus, while there is value in conditioning active share (especially on prior performance), the gap in return predictability between U.S. and non-U.S. portfolios not only remains, but is in fact even larger than before, leaving the puzzle unresolved. Moreover, prior performance itself is (at best) an indirect proxy for managerial skill and it may also be related to other fund characteristics, such as anomaly tilts, that generate short-term performance persistence. Prior performance is also far less than persistent than anomaly tilts, which is not only more expensive through loads (common outside of the U.S.), but it also requires investor awareness.[13]

[Table 9]

[13] In our sample, 15% [57%] of North American [European]-sold funds are classified as load funds.

5 Conclusions

It is now well debated whether active share predicts returns in U.S. equity mutual funds. However, active share remains a strong return predictor in domestic equity funds outside the U.S. Why?

We reconcile these differences between U.S. and international markets by analyzing the value of active share in global equity funds. These funds invest roughly equal proportions in U.S. and non-U.S. equity markets. We analyze the relation between active share and future returns in the U.S. portion of a global fund relative to other regions of the same fund, and find that active share is a strong predictor only in Europe and Asia-Pacific, but not in the United States. These results also carry over to the fund level: highly active global funds (with large U.S. allocation) outperform only marginally, while highly active global ex-U.S. funds outperform very strongly.

We rule out several alternative explanations proposed in the literature. First, by holding constant the investment mandate and manager location, we rule out an alternative explanation based on differential access to global information between U.S. and non-U.S. managers (Albuquerque et al. (2009)). Since global funds only have a minimal allocation to the market in which they are sold, we can also eliminate the possibility of a home-country advantage (e.g., Demirci et al. (2022)). Factors related to investor behavior or time-varying arbitrage capital cannot explain our findings either, since we find comparable results regardless of region of sale (equivalent to manager location). The traditional approach of conditioning active share on holding horizon, or prior performance, does not help either, as doing so only serves to magnify the gap in return predictability between U.S. and non-U.S. regions.

Instead, we connect the weakness of active share as a return predictor in the United States to trading on asset pricing anomalies. Avramov et al. (2020) show that the return predictability of activeness in U.S. equity funds depends tilting towards rather than against anomalies. In our setting, we find that higher active share in U.S. stocks by global equity funds is, on average, associated with significantly lower anomaly tilts, while the opposite is true in Asia-Pacific (the relation is insignificant in Europe). Considering interactions of active share and anomaly tilts, we find strong evidence that high active share portfolios with high anomaly tilts outperform low active share portfolios with low tilts across all three regions of the world. While the return predictability remains stronger in Europe and Asia-Pacific, it is both statistically and economically significant in the United States as well.

Overall, our results suggest that the weakness of active share in recent studies of U.S. equity funds is unique to the underlying U.S. equity markets, and is not explained by omitted U.S. country attributes related to investor or manager behavior, or to the availability of arbitrage capital. Our results also highlight the importance of conditioning active share on the fund's anomaly tilt in order to better reveal the value added that active managers create. As Berk and van Binsbergen (2015) point out, even if active managers deliver alpha via anomaly exposure, we should treat it as value added for investors if they cannot reproduce the same anomaly exposures themselves. This is especially true given the importance of real-word implementation costs (e.g., Frazzini, Israel, and Moskowitz (2018), Chen and Velikov (2022)), and the poor track record of factor-based ETFs (e.g., Huang, Song and Xiang (2022), and Broman and Moneta (2024)).

References

Albuquerque, R., Bauer, G. H., & Schneider, M. (2009). Global private information in international equity markets. *Journal of Financial Economics*, 94, 18-46.

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

Avramov, D., Cheng, S., & Hameed, A. (2020). Mutual funds and mispriced stocks. *Management Science*, 66(6), 2372-2395.

Baltussen, G., Swinkels, L., & Van Vliet, P. (2021). Global factor premiums. *Journal of Financial Economics*, 142(3), 1128-1154.

Berk, J., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, 112(6), 1269-1295.

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

Betermier, S., Schumacher, D., & Shahrad, A. (2023). Mutual Fund Proliferation and Entry Deterrence. *Review of Asset Pricing Studies* 13, 784-829.

Bhattacharya, U., & Galpin, N. (2011). The global rise of the value-weighted portfolio. *Journal of Financial and Quantitative Analysis*, 46(3), 737-756.

Briere, M., Lehalle, C. A., Nefedova, T., & Raboun, A. (2019). Stock market liquidity and the trading costs of asset pricing anomalies. Université Paris-Dauphine Research Paper.

Broman, M., Densmore, M., & Shum Nolan, P. (2023). The Geography of Subadvisors, Managerial Structure, and the Performance of International Equity Mutual Funds. *Review of Asset Pricing Studies*, 13, 343-374.

Broman, M. & Lovelace, K. (2024). *A U-Shaped Flow-Performance Sensitivity Across the Globe*. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4734646

Broman, M., & Moneta, F. (2024). On the Anomaly Tilts of Factor Funds. *Financial Management*, 53(3), 605-635.

Buffa, A. M., & Javadekar, A. (2022). *A Signaling Theory of Mutual Fund Activeness*. Indian School of Business.

Buffa, A. M., Vayanos, D., & Woolley, P. (2022). Asset management contracts and equilibrium prices. *Journal of Political Economy*, 130, 3146-3201.

Busse, J. A., Goyal, A., & Wahal, S. (2014). Investing in a global world. *Review of Finance*, 18(2), 561-590.

Carhart, M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82.

Cao, J., Han, B., & Wang, Q. (2017). Institutional investment constraints and stock prices. *Journal of Financial and Quantitative Analysis*, 52(2), 465-489.

Cella, C., Ellul, A., & Giannetti, M. (2013). Investors' horizons and the amplification of market shocks. *Review of Financial Studies*, 26, 1607-1648.

Chakraborty, I., Kumar, A., Muhlhofer, T., & Sastry, R. (2020). *Heuristic fund allocation decisions*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2869426

Chen, A. Y., & Velikov, M. (2022). Zeroing in on the Expected Returns of Anomalies. *Journal of Financial and Quantitative Analysis* 58, 1-83.

Choi, J., Cremers, M., & Riley, T. B. (2023). *Why Have Actively Managed Bond Funds Remained Popular?* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3557235

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

Cowan, A. R., & Salotti, V. (2020). Anti-selective disclosure regulation and analyst forecast accuracy and usefulness. *Journal of Corporate Finance*, 64, 101669.

Cremers, M., Ferreira, M. A., Matos, P., & Starks, L. (2016). Indexing and active fund management: International evidence. *Journal of Financial Economics* 120, 539-560.

Cremers, K. M., Fulkerson, J. A., & Riley, T. B. (2022). Active share and the predictability of the performance of separate accounts. *Financial Analysts Journal*, 78, 39-57.

Cremers, M., & Pareek, A. (2016). Patient capital outperformance: The investment skill of high active share managers who trade infrequently. *Journal of Financial Economics*, 122, 288-306.

Cui, X., Kolokolova, O., & Wang, J. (2024). On the other side of hedge fund equity trades. *Management Science*, 70(6), 3684-3710.

Cremers, K. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, 22, 3329-3365.

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

Demirci, I., Ferreira, M. A., Matos, P., & Sialm, C. (2022). How global is your mutual fund? International diversification from multinationals. *Review of Financial Studies*, 35, 3337-3372.

Doshi, H., Elkamhi, R., & Simutin, M. (2015). Managerial activeness and mutual fund performance. *Review of Asset Pricing Studies*, 5, 156-184.

Dyakov, T., Jiang, H., & Verbeek, M. (2020). Trade less and exit overcrowded markets: Lessons from international mutual funds. *Review of Finance*, 24, 677-731.

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

Evans, R., Gómez, J. P., Ma, L., & Tang, Y. (2023). Peer versus pure benchmarks in the compensation of mutual fund managers. *Journal of Financial and Quantitative Analysis*, forthcoming.

Evans, R., & Sun, Y. (2021). Models or stars: The role of asset pricing models and heuristics in investor risk adjustment. *Review of Financial Studies*, 34, 67-107.

Fama, E., & French, K. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105, 457-472.

Fama, E., & French, K. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, 123, 441-463.

Ferreira, M., Keswani, A., Miguel, A., & Ramos, S. (2012). The Flow-Performance Relationship around the World. *Journal of Banking & Finance* 36, 1759-1780.

Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2013). The determinants of mutual fund performance: A cross-country study. *Review of Finance*, 17, 483-525.

Frazzini, A., Israel, R., & Moskowitz, T. J. (2018). *Trading costs*. Available at SSRN 3229719.

Gao, X., & Wang, Y. (2023). Mining the short side: Institutional investors and stock market anomalies. *Journal of Financial and Quantitative Analysis*, 58(1), 392-418.

Gaspar, J. M., Massa, M., & Matos, P. (2005). Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics*, 76, 135-165.

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

Hollstein, F. (2022). Local, regional, or global asset pricing?. *Journal of Financial and Quantitative Analysis*, 57, 291-320.

Huang, S., Song, Y., & Xiang, H. (2020). The smart beta mirage. *Journal of Financial and Quantitative Analysis*, 1-69.

ICI (2022): 2022 Investment Company Factbook: A Review of Trends and Activities in the Investment Company Industry. Available at: https://www.ici.org/doc-server/pdf:2022_factbook.pdf

Irvine, P., Kim, J., & Ren, J. (2022). The beta anomaly and mutual fund performance. *Management Science* 70, 143-163.

Jacobs, H., & Müller, S. (2020). Anomalies across the globe: Once public, no longer existent?. *Journal of Financial Economics* 135, 213-230.

Jagannathan, M., Jiao, W., & Karolyi, G. A. (2022). Is there a home field advantage in global markets?. *Journal of Financial Economics*, 143(2), 742-770.

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

Jiang, H., & Sun, Z. (2014). Dispersion in beliefs among active mutual funds and the cross-section of stock returns. *Journal of Financial Economics*, 114, 341-365.

Jiao, W., Karolyi, G., & Ng, D. (2022). *Can International Funds Navigate Changing Global Investment Environments*?. Available at SSRN 4052003.

Joenväärä, J., & Kosowski, R. (2021). The effect of regulatory constraints on fund performance: New evidence from UCITS hedge funds. *Review of Finance*, 25(1), 189-233.

Jones, C., & Mo, H. (2021). Out-of-sample performance of mutual fund predictors. *Review of Financial Studies*, 34, 149-193.

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

Kacperczyk, M., Sundaresan, S., & Wang, T. (2021). Do foreign institutional investors improve price efficiency?. *The Review of Financial Studies*, 34, 1317-1367.

Keswani, A., Medhat, M., Miguel, A., Ramos, S., (2020). Uncertainty Avoidance and Mutual Funds. *Journal of Corporate Finance* 65, 101748.

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.

Khorana, A., Servaes, H., & Tufano, P. (2005). Explaining the Size of the Mutual Fund Industry around the World. *Journal of Financial Economics* 78, 145–85.

Khorana, A., Servaes, H., & Tufano, P. (2009). Mutual fund fees around the world. *Review of Financial Studies,* 22, 1279-1310.

Lan, C., Moneta, F., & Wermers, R. (2023). Holding horizon: a new measure of active investment management. *Journal of Financial and Quantitative Analysis*, 1-45.

Lantushenko, V., & Nelling, E. (2021). Do more active funds still earn higher performance? Evidence from Active Share over time. *Journal of Financial Research*, 44, 725-752.

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

Lu, X., Stambaugh, R., & Yuan, Y. (2017). *Anomalies abroad: Beyond data mining* (No. w23809). National Bureau of Economic Research.

McLean, R., & Pontiff, J. (2016). Does academic research destroy stock return predictability?. *Journal of Finance*, 71, 5-32.

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

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

Sias, R., Turtle, H. J., & Zykaj, B. (2016). Hedge fund crowds and mispricing. *Management Science*, 62(3), 764-784.

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

Van Nieuwerburgh, S., & Veldkamp, L. (2009). Information immobility and the home bias puzzle. *Journal of Finance*, 64, 1187-1215.

von Reibnitz, A. (2017). When Opportunity Knocks: Cross-Sectional Return Dispersion and Active Fund Performance. *Critical Finance Review*, 6, 303-356.

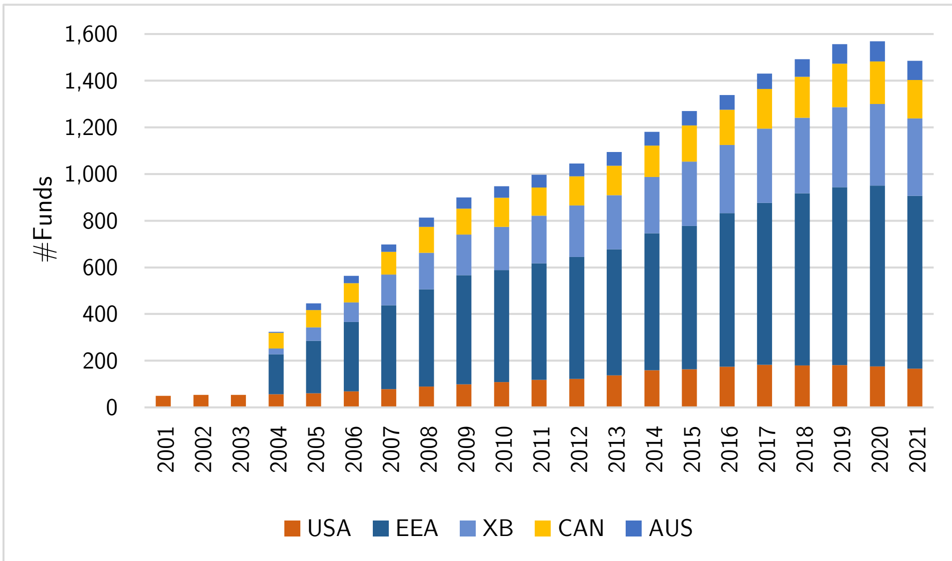
Wahal, S., & Wang, A. (2011). Competition among mutual funds. *Journal of Financial Economics*, 99, 40-59.

Wang, Z. J., Zhang, H., & Zhang, X. (2020). Fire sales and impediments to liquidity provision in the corporate bond market. *Journal of Financial and Quantitative Analysis*, 55(8), 2613-2640.

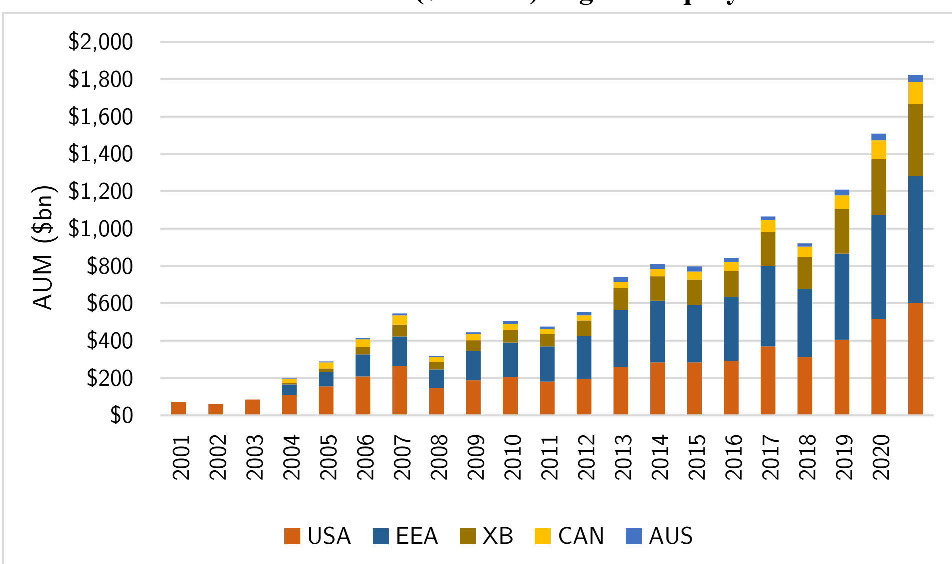
Figure 1: Total number of funds by region of sale

The figures below illustrate the total number and AUM (in $billions) of global equity funds in Panels A and B, and the corresponding numbers for global ex-U.S. equity funds in Panels C and D. The regions of sale are United States (USA), Europe (EEA), Europe Cross-border (XB), Canada (CAN) and Australia (AUS).

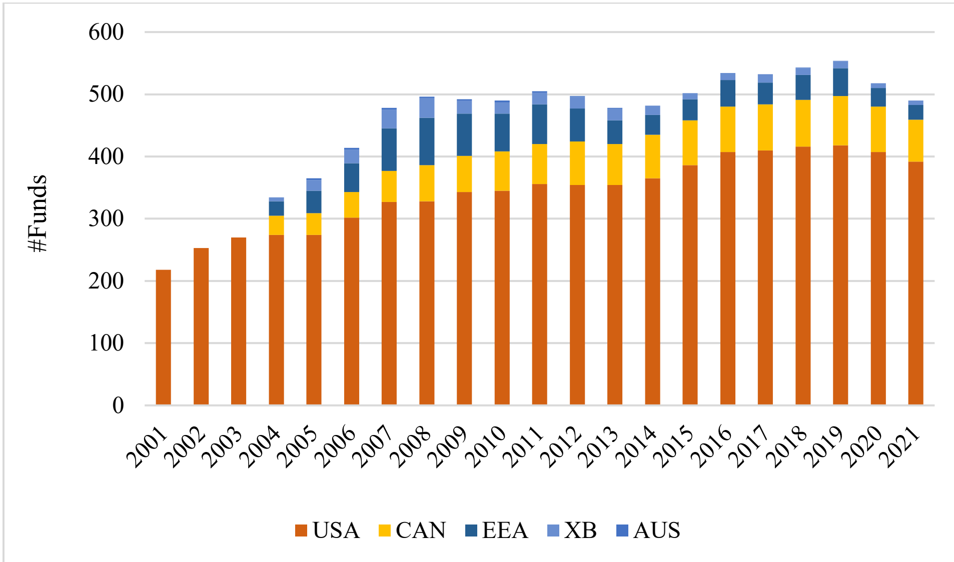
Panel A: Total number of global equity funds



Panel B: Total AUM ($billions) of global equity funds



Panel C: Total number of global ex-U.S. equity funds



Panel D: AUM ($billions) of global ex-U.S. equity funds

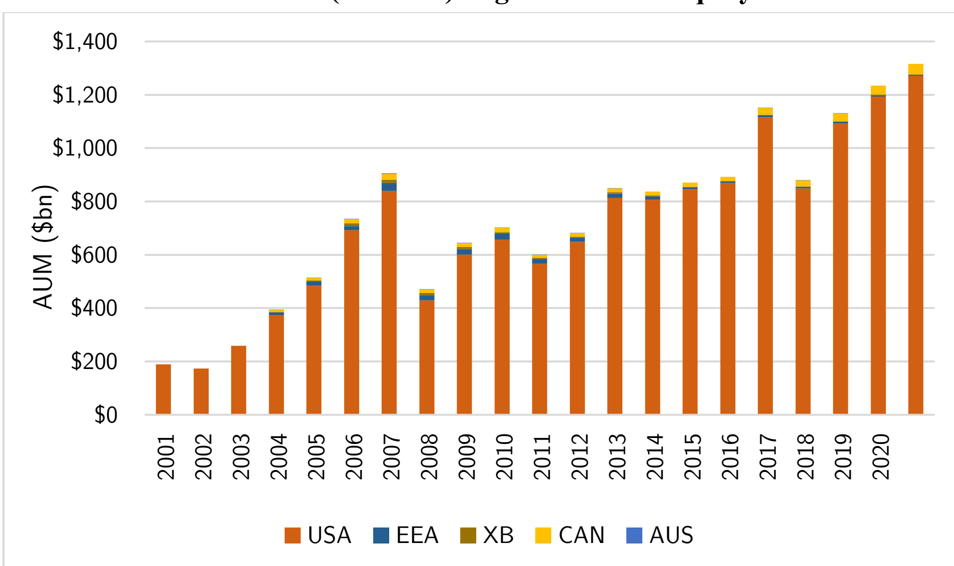


Table 1: Total Number of Funds and AUM

In Panel A, we present summary statistics for the number of funds (#Funds) and the total Assets Under Management (AUM; in $billions) by country of sale. The Cross-border label refers to funds that are sold across Europe, or Globally. All other funds are available for sale in a single country. Panel B summarizes the proportion of global and global ex-US equity fund-month observations by region of sale.

	2005		2013		2021	
Country of sale	#Funds	AUM ($b)	#Funds	AUM ($b)	#Funds	AUM ($b)
Australia	32	6.37	61	25.75	83	38.65
North America						
Canada	109	41.77	192	49.22	231	159.78
United States	335	639.90	491	1070.32	558	1870.20
Europe						
Austria	6	0.49	32	2.61	43	9.48
Belgium	2	0.14	25	6.60	22	18.85
Denmark	36	6.73	61	16.21	85	40.95
Finland	7	0.41	11	3.99	18	11.88
France	17	4.13	28	15.68	60	40.94
Germany	62	35.15	91	58.33	114	159.48
Italy	17	3.27	16	3.27	26	16.17
Netherlands	9	12.48	26	24.84	47	43.19
Norway	9	3.14	21	14.58	24	23.90
Portugal			3	0.13	4	2.79
Sweden	23	0.82	14	0.80	35	6.13
Spain	2	0.41	30	38.10	40	49.16
Switzerland	12	1.65	38	6.45	52	17.32
United Kingdom	54	18.62	177	129.42	198	246.26
Cross-border	70	20.72	251	123.37	344	412.69
Total	802	796.19	1568	1589.67	1984	3167.82

Panel B: Proportion of Global and Global ex-US Equity funds

Region of sale	Global	Global ex-US
Australia	98.3%	1.7%
Canada	68.1%	31.9%
United States	25.5%	74.5%
Europe: single country of sale	93.7%	6.3%
Europe: cross-border	94.1%	5.9%

Table 2: Summary Statistics for Measures of Portfolio Activeness

We provide summary statistics for the full sample (Panel A), and separately by country of sale (Panel B). *Active share* is computed relative to a benchmark index (BBMK), or relative to style peers (PEER). When computing the former, we use broad-based market-cap weighted benchmarks based on the corresponding Vanguard index fund. The benchmark for the latter (PEER) corresponds to the aggregate portfolio of global/global ex-US equity funds in the same style category (Morningstar Category) and sold in the same region. *Anomaly tilts* measure the extent to which a portfolio is tilted towards nine well-known asset pricing anomalies (Stambaugh et al. (2012)). Similar to Avramov, Cheng and Hameed (2020), we compute for each stock the characteristic (decile) scores on a particular anomaly (e.g., momentum). Fund-level anomaly 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 benchmark index fund, and then averaged across the nine anomalies. As a measure of fund holding horizon, we use the *Churn Ratio* by Gaspar, Massa, and Matos (2005) and Cella, Ellul, and Giannetti (2013). Control variables include fund *age* since inception, Assets Under Management (*AUM*), fund *family AUM*, the *% expense ratio*, yearly % *net fund flows*, and %*tracking error*.

Panel A: Full sample descriptive statistics

	AVG	STD	P25	MD	P75
%Active Share (BBMK)	85.63	12.27	81.03	88.73	93.92
%Active Share (PEER)	83.10	11.45	77.50	85.32	91.26
%Churn Ratio	34.19	26.19	16.52	27.41	43.77
Anomaly Tilt (deciles)	0.07	0.28	-0.08	0.09	0.25
Control variables					
Age (years)	12.31	8.83	5.54	10.34	16.91
AUM ($b)	0.84	2.64	0.05	0.17	0.57
Family AUM ($b)	63.18	143.64	2.16	16.30	60.81
%Expense Ratio	1.41	0.63	0.98	1.35	1.78
%Net Flow	4.70	33.27	-13.85	-1.64	16.85
%Tracking error	1.51	0.67	1.05	1.37	1.80

Panel B: Distribution by country of sale

	%Active Share (BBMK)			%Active Share (PEER)			Anomaly Tilt		
	P25	P50	P75	P25	P50	P75	P25	P50	P75
Australia	74.2	86.5	92.9	71.1	82.7	89.0	-0.11	0.08	0.26
North America									
Canada	83.5	90.1	95.3	79.9	86.8	92.1	-0.11	0.08	0.26
United States	78.2	87.8	94.6	75.4	83.9	91.2	-0.08	0.08	0.23
Europe									
Austria	83.0	88.2	92.8	79.8	85.7	90.9	0.00	0.16	0.32
Belgium	81.6	89.0	94.8	79.1	87.2	93.8	-0.15	0.06	0.22
Denmark	82.8	88.8	93.0	76.5	84.4	90.0	0.04	0.17	0.31
Finland	82.8	92.5	96.9	77.5	88.9	97.2	-0.09	0.15	0.30
France	81.5	89.1	94.6	77.9	85.9	92.1	-0.16	0.05	0.19
Germany	79.5	87.7	93.3	76.0	84.8	92.1	-0.04	0.13	0.28
Italy	67.1	81.6	88.2	66.7	78.2	84.5	-0.04	0.09	0.20
Netherlands	79.9	85.7	91.3	75.7	82.0	87.4	-0.05	0.12	0.28
Norway	85.0	91.2	94.9	81.8	88.6	92.9	-0.08	0.06	0.24
Portugal	79.5	84.4	89.1	78.7	82.8	88.1	-0.19	0.09	0.35
Spain	81.5	90.7	95.5	78.9	88.3	94.0	-0.21	0.07	0.24
Sweden	70.0	86.4	92.0	69.0	83.4	89.7	0.03	0.16	0.30
Switzerland	78.5	86.8	92.1	76.5	84.2	90.4	-0.01	0.14	0.30
U.K.	85.0	90.2	93.7	81.4	87.3	91.4	-0.12	0.06	0.25
Cross-border	84.0	89.7	93.6	80.0	86.1	91.2	-0.10	0.08	0.26
Full	81.0	88.7	93.9	77.5	85.3	91.3	-0.08	0.09	0.25

Table 3: The Return Predictability of Active Share by Investment Mandate

This table reports the results for pooled OLS regressions of fund performance on lagged measures of fund activeness and control variables, estimated separately by investment mandate (Global or Global ex-U.S.). We assess fund performance using a factor-based risk adjustment (CAPM, Fama-French-Carhart 4-factor or Fama-French 6 factor), and a benchmark-based adjustment. Active share is measured relative to broad-based benchmarks (Panel A), or the aggregate portfolio of style peers sold in the same region (Panel B). The continuous measure of active share is based on percentile ranks (ranging from 0 to 1), while the discrete measure is based on quintile dummies (Q2-Q5; Q1 omitted). The following control variables are also included: fund age, AUM, family AUM, net fund flow (*Net Flow*) over the prior 12 months, the annual net expense ratio (*Exp. Ratio*), and tracking error (*Track. Err.*). All specifications include style and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: Active share vis-à-vis broad benchmarks

	CAPM alpha		FFC4 alpha		FF6 alpha		Bmk.-adj. alpha	
AS Quintile	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Q2	0.0260*	0.0213	0.0125	0.0204	0.0050	0.0214	0.0149	0.0152
	(1.74)	(1.52)	(0.89)	(1.53)	(0.33)	(1.48)	(0.94)	(0.99)
Q3	0.0478***	0.0382**	0.0291*	0.0537***	0.0293*	0.0439**	0.0346*	0.0543***
	(2.77)	(1.98)	(1.78)	(2.99)	(1.73)	(2.30)	(1.83)	(2.65)
Q4	0.0579***	0.0797***	0.0498**	0.0807***	0.0500**	0.0492*	0.0578***	0.1007***
	(2.62)	(2.85)	(2.52)	(3.25)	(2.36)	(1.92)	(2.65)	(3.40)
Q5	0.0669**	0.1465***	0.0649**	0.1317***	0.0636**	0.1249***	0.0690**	0.1764***
	(2.00)	(4.08)	(2.33)	(4.19)	(2.15)	(3.73)	(2.22)	(4.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Style	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.057	0.138	0.055	0.172	0.087	0.203	0.115	0.160
N	209,872	98,425	209,872	98,425	209,872	98,425	212,303	100,608

Panel B: Active share vis-à-vis style peers								
	CAPM alpha		FFC4 alpha		FF6 alpha		Bmk.-adj. alpha	
Quintile	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Q2	0.0562***	0.0433**	0.0362***	0.0316**	0.0504***	0.0278*	0.0192	0.0184
	(3.60)	(2.28)	(2.72)	(2.09)	(3.57)	(1.69)	(1.29)	(1.03)
Q3	0.0709***	0.0849***	0.0430***	0.0657***	0.0635***	0.0576***	0.0269	0.0515**
	(4.05)	(3.49)	(2.86)	(3.32)	(3.96)	(2.85)	(1.51)	(2.23)
Q4	0.0701***	0.1560***	0.0592***	0.1282***	0.0700***	0.0876***	0.0439**	0.1088***
	(3.55)	(4.70)	(3.27)	(4.92)	(3.57)	(3.30)	(2.09)	(3.75)
Q5	0.0378	0.2134***	0.0427	0.1639***	0.0449*	0.1034***	0.0513*	0.1296***
	(1.11)	(4.40)	(1.56)	(4.42)	(1.70)	(3.05)	(1.75)	(3.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Style	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.053	0.136	0.055	0.173	0.086	0.203	0.116	0.161
N	208,283	98,325	208,283	98,325	208,283	98,325	210,400	100,418

Table 4: Decomposing the Return Predictability at the Regional Sub-Portfolio Level

This table reports the results for regressions of regional sub-portfolio risk-adjusted performance on quintile dummies for regional active share (broad-based benchmarks) and control variables. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe, and iii) Asia-Pacific. Control variables are the same as in Table 3, including fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. All specifications include style, investment mandate (i.e., global or global ex-U.S.), and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

	CAPM			FFC4		
AS quintile	United States	Europe	Asia-Pacific	United States	Europe	Asia-Pacific
Q2	-0.0050	0.0115	0.0533***	-0.0050	-0.0055	0.0528***
	(0.37)	(1.11)	(3.51)	(0.39)	(0.55)	(3.50)
Q3	-0.0033	0.0131	0.0753***	-0.0043	0.0055	0.0753***
	(0.24)	(1.24)	(4.85)	(0.33)	(0.54)	(4.89)
Q4	-0.0201	0.0689***	0.0629***	-0.0261*	0.0537***	0.0644***
	(1.41)	(6.29)	(3.97)	(1.95)	(5.07)	(4.10)
Q5	-0.0261	0.1471***	0.1224***	-0.0200	0.1071***	0.1203***
	(1.64)	(11.25)	(6.42)	(1.34)	(8.47)	(6.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Mandate	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.045	0.074	0.154	0.041	0.078	0.152
N	193,996	282,851	193,995	193,996	282,851	193,995

	FF6 alpha			BMK-adj. Alpha		
AS quintile	United States	Europe	Asia-Pacific	United States	Europe	Asia-Pacific
Q2	-0.0031	-0.0037	0.0672***	-0.0034	0.0170	0.0524***
	(0.24)	(0.35)	(4.19)	(0.25)	(1.57)	(3.24)
Q3	-0.0063	0.0066	0.0821***	-0.0005	0.0226**	0.0937***
	(0.48)	(0.62)	(5.02)	(0.04)	(2.06)	(5.67)
Q4	-0.0321**	0.0462***	0.0745***	-0.0174	0.0834***	0.0840***
	(2.37)	(4.16)	(4.46)	(1.22)	(7.31)	(4.98)
Q5	-0.0173	0.0865***	0.1412***	-0.0234	0.1620***	0.1551***
	(1.15)	(6.52)	(7.02)	(1.47)	(11.90)	(7.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Mandate	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.044	0.077	0.283	0.038	0.069	0.108
N	193,996	282,851	193,995	193,996	283,834	194,900

Table 5: Regional Active Share and Anomaly Tilts

This table reports the results for regressions of sub-portfolio risk-adjusted performance on active share interacted with anomaly tilts. We discretize active share and its interactions by using the top (*High*) and bottom (*Low*) tercile. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe, and iii) Asia-Pacific. Each of the three panels presents results for one sub-portfolio. Results are estimated separately by region of sale (ROS), and by global/global ex-U.S. equity (only in Panels B and C). Control variables are the same as in Table 3 and include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. All specifications include style and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: CAPM alpha

	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0456***	-0.0602***	-0.0516***	-0.1331***	-0.0849***
	(2.83)	(2.95)	(2.91)	(3.86)	(3.32)
Low × High	0.0577***	0.0265	0.0228	0.0171	0.0240
	(4.31)	(1.45)	(1.08)	(0.57)	(0.85)
High × Low	-0.0603***	-0.0276	-0.0041	-0.1167***	-0.1622***
	(4.81)	(0.93)	(0.12)	(2.81)	(4.16)
High × High	0.0681***	0.1632***	0.1982***	0.0840**	0.1175***
	(4.63)	(6.47)	(6.16)	(2.57)	(3.37)
Difference between High × High and Low × Low					
	0.1137***	0.2233***	0.2498***	0.2171***	0.2024***
	(5.54)	(6.48)	(6.39)	(4.18)	(4.73)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.079	0.083	0.147	0.171
N	193,562	186,076	96,507	106,840	86,935

Panel B: FFC4 alpha

	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0195	-0.0319*	-0.0197	-0.1082***	-0.0938***
	(1.28)	(1.77)	(1.13)	(3.42)	(3.82)
Low × High	0.0518***	0.0137	-0.0274	0.0106	0.0161
	(4.11)	(0.79)	(1.55)	(0.35)	(0.58)
High × Low	-0.0359***	-0.0075	0.0245	-0.0981**	-0.1841***
	(3.04)	(0.29)	(0.85)	(2.55)	(5.30)
High × High	0.0561***	0.1246***	0.1459***	0.0967***	0.1005***
	(4.04)	(5.28)	(4.91)	(3.08)	(3.24)
Difference between High × High and Low × Low					
	0.0756***	0.1565***	0.1656***	0.2048***	0.1943***
	(3.90)	(4.97)	(4.56)	(4.38)	(4.87)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.038	0.078	0.090	0.142	0.171
N	193,562	186,076	96,507	106,840	86,935

Panel C: FF6 alpha					
	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0233	-0.0334*	-0.0064	-0.1134***	-0.1043***
	(1.51)	(1.74)	(0.35)	(3.27)	(3.79)
Low × High	0.0452***	-0.0055	-0.0333*	0.0072	-0.0081
	(3.54)	(0.30)	(1.82)	(0.22)	(0.26)
High × Low	-0.0394***	0.0019	-0.0058	-0.0536	-0.1355***
	(3.30)	(0.07)	(0.19)	(1.29)	(3.73)
High × High	0.0461***	0.0975***	0.1312***	0.0700**	0.0665**
	(3.29)	(4.18)	(4.54)	(2.20)	(2.09)
Difference between High × High and Low × Low					
	0.0694***	0.1309***	0.1376***	0.1833***	0.1708***
	(3.54)	(4.12)	(3.86)	(3.58)	(4.05)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.038	0.073	0.099	0.272	0.303
N	193,562	186,076	96,507	106,840	86,935

Table 6: Active Share and Anomaly Tilts: Fund-level Results

This table reports the results for pooled OLS regressions of fund performance on lagged measures of active share (broad-based) interacted with anomaly tilts and control variables. Results are presented separately by investment mandate. Controls variables (omitted for brevity) are the same as in Table 3. All specifications include style and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

	CAPM alpha		FFC4 alpha		FF6 alpha		Bmk.-adj. alpha	
AS × Anomaly	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Low × Low	-0.0657***	-0.0580***	-0.0430***	-0.0325**	-0.0464***	-0.0106	-0.0789***	-0.0573***
	(4.06)	(3.73)	(3.05)	(2.37)	(3.17)	(0.78)	(4.72)	(3.43)
Low × High	0.0195	0.0049	0.0092	-0.0308*	-0.0019	-0.0340**	0.0256	-0.0130
	(1.16)	(0.26)	(0.61)	(1.93)	(0.12)	(2.03)	(1.42)	(0.65)
High × Low	-0.0443*	-0.0858***	0.0012	-0.0465*	0.0081	-0.0425	-0.0332	-0.0488
	(1.66)	(2.77)	(0.06)	(1.75)	(0.40)	(1.50)	(1.34)	(1.50)
High × High	0.1025***	0.1560***	0.0801***	0.1043***	0.0667***	0.0573**	0.1077***	0.1615***
	(4.70)	(5.83)	(3.94)	(4.32)	(3.13)	(2.29)	(5.13)	(5.80)
Difference between High × High and Low × Low								
	0.1683***	0.2140***	0.1231***	0.1368***	0.1131***	0.0680**	0.1866***	0.2189**
	(5.79)	(6.45)	(4.60)	(4.59)	(4.06)	(2.28)	(6.35)	(6.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Style	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.136	0.055	0.169	0.083	0.198	0.117	0.158
N	229,331	103,679	229,331	103,679	229,331	103,679	232,967	106,374

Table 7: Determinants of Active Share

In Panel A, we report the results for pooled OLS regressions of regional sub-portfolio active share on regional anomaly tilts. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe (EU), and iii) Asia-Pacific (ASPA). Active share and anomaly tilts are both measured at the regional sub-portfolio level. In Panel B, we instead estimate regressions of fund-level active share on the fund's regional sub-portfolio anomaly tilts (US, EU and Asia-Pacific). In both Panels, the control variables are the same and include fund age, AUM, family AUM, net fund flow over the prior 12 months, the tracking error, the annual net expense ratio, and tracking error. All specifications include style and time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: Y = Regional Sub-portfolio Active Share (broad-based)

	Global ex-U.S.	Global equity		
	ROS = All	ROS = All	ROS = NA	ROS = EU
Variables	(1)	(2)	(3)	(4)
Anomaly Tilt × US		-1.215***	-1.051***	-1.137***
		(8.08)	(4.75)	(6.77)
Anomaly Tilt × EU	0.143	0.085	0.193	0.027
	(0.67)	(0.66)	(0.88)	(0.20)
Anomaly Tilt × ASPA	1.441***	2.109***	1.156***	2.123***
	(6.13)	(8.75)	(3.33)	(7.93)
US dummy		-1.937***	-2.887***	-1.757***
		(8.94)	(9.24)	(6.73)
ASPA dummy	6.451***	3.903***	2.401***	4.387***
	(23.63)	(18.89)	(6.52)	(17.61)
ln(Age)	0.759**	-0.419*	0.206	-0.408
	(2.47)	(1.94)	(0.51)	(1.62)
ln(AUM)	-1.052***	-0.748***	-0.448	-1.241***
	(2.99)	(3.00)	(1.10)	(4.22)
ln(FAMILY AUM)	-0.845***	-0.114	-0.737*	0.142
	(2.59)	(0.48)	(1.74)	(0.53)
Exp. Ratio	1.279***	1.520***	1.214***	0.752**
	(3.58)	(5.41)	(3.63)	(2.33)
Net Flow	0.524***	0.158	0.408**	0.175
	(3.33)	(1.39)	(2.00)	(1.33)
Track. Err	4.127***	3.041***	3.468***	3.515***
	(11.73)	(9.51)	(9.74)	(12.81)
Fixed effects				
Style	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Adjusted R2	0.463	0.276	0.340	0.281
N	171,890	483,949	119,823	339,411

Panel B: Y = Fund-level Active Share [broad-based]				
	Global ex-U.S.		Global Equity funds	
Variables	(1)	(2)	(3)	(4)
Anomaly tilt	0.8288***		-0.3559**	
	(4.41)		(2.51)	
Anomaly tilt (US subp.)				-1.5204***
				(7.45)
Anomaly tilt (EU subp.)		-0.5937***		-0.2376
		(3.02)		(1.47)
Anomaly tilt (ASPA subp.)		1.5114***		2.3463***
		(7.08)		(9.26)
ln(Age)	0.6740**	0.7509**	-0.6234***	-0.2874
	(2.14)	(2.28)	(2.80)	(0.88)
ln(AUM)	-1.0283***	-1.0276***	-0.6332***	-0.8872***
	(3.12)	(2.98)	(2.75)	(2.72)
ln(FAMILY AUM)	-0.6938**	-0.8478**	-0.1945	-0.2054
	(2.32)	(2.56)	(0.88)	(0.55)
Exp. Ratio	1.1588***	1.1613***	1.5528***	1.6428***
	(3.65)	(3.36)	(6.11)	(4.22)
Net Flow	0.4958***	0.5740***	0.1667	-0.1119
	(3.35)	(3.48)	(1.56)	(0.63)
Track. Err	4.4197***	4.3881***	3.5490***	3.7578***
	(13.83)	(11.52)	(11.79)	(6.66)
Fixed effects				
Style	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Adjusted R2	0.472	0.489	0.291	0.332
N	97,760	86,097	209,549	108,237

Table 8: Fund Activeness and Other Conditioning Information

This table reports the results for pooled OLS regressions of fund performance on lagged measures of active share interacted with fund holdings horizon as measured by the churn ratio (Panel A), or prior 36-month performance (Panel B), and control variables. In Panel A, the label "High" for holding horizon corresponds to low churn ratios. Controls variables (omitted for brevity) include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. All specifications include style and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: Active Share (broad-based benchmarks) × Holding Horizon

	CAPM alpha		FFC4		FF6	
	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Low × Low	-0.0332**	-0.0296*	-0.0310**	-0.0692***	-0.0381***	-0.0605***
	(2.17)	(1.73)	(2.24)	(4.48)	(2.59)	(3.86)
Low × High	-0.0106	-0.0069	-0.0024	0.0080	-0.0014	0.0156
	(0.73)	(0.48)	(0.19)	(0.62)	(0.10)	(1.15)
High × Low	-0.0074	0.0245	-0.0081	-0.0124	0.0074	-0.0231
	(0.33)	(0.82)	(0.42)	(0.48)	(0.35)	(0.80)
High × High	0.0699***	0.0559**	0.0638***	0.0193	0.0495***	-0.0103
	(3.41)	(2.16)	(3.53)	(0.86)	(2.62)	(0.43)
Difference between High × High and Low × Low						
	0.1031***	0.0854***	0.0948***	0.0885***	0.0876***	0.0501*
	(3.64)	(2.64)	(3.92)	(3.12)	(3.41)	(1.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.135	0.055	0.168	0.083	0.198
N	229,331	103,679	229,331	103,679	229,331	103,679

Panel B: Active Share (broad-based benchmarks) × Past Performance

	CAPM alpha		FFC4		FF6	
	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Low × Low	-0.0478**	-0.0727***	-0.0203	-0.0688***	-0.0387**	-0.0710***
	(2.57)	(4.27)	(1.30)	(4.34)	(2.25)	(4.54)
Low × High	0.0011	0.0352	-0.0129	-0.0110	-0.0186	0.0161
	(0.05)	(1.48)	(0.70)	(0.61)	(0.99)	(0.93)
High × Low	-0.0766**	-0.1221***	-0.0098	-0.0347	-0.0282	-0.0712***
	(2.32)	(3.73)	(0.46)	(1.38)	(1.21)	(2.73)
High × High	0.0794***	0.1441***	0.0995***	0.1322***	0.0897***	0.1083***
	(3.12)	(4.62)	(5.28)	(5.49)	(4.49)	(4.28)
Difference between High × High and Low × Low						
	0.1272***	0.2168***	0.1197***	0.2010***	0.1284***	0.1793**
	(3.70)	(5.71)	(4.60)	(6.51)	(4.63)	(5.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.137	0.055	0.169	0.084	0.199
N	229,331	103,679	229,331	103,679	229,331	103,679

Table 9: Regional Sub-Portfolio Activeness and Other Conditioning Information

This table reports the results for regressions of sub-portfolio risk-adjusted performance on active share, its interactions and control variables. Active share is interacted with fund holdings horizon (as measured by the churn ratio), or past performance (36 months). We discretize active share and its interactions by using the top and bottom tercile. In Panel A, the label "Hi" for Holding Horizon corresponds to the bottom tercile on churn ratios. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States (US), ii) Europe (EU), and iii) Asia-Pacific (ASPA). Control variables are the same as in Table 3. All specifications include style, mandate (global vs. global ex-U.S.) and calendar time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: Active Share (broad-based benchmarks) × Holding Horizon

	CAPM			FFC4		
	United States	Europe	Asia-Pacific	United States	Europe	Asia-Pacific
Low × Low	0.0150	-0.0149	-0.0517***	0.0123	-0.0279***	-0.0585***
	(1.10)	(1.36)	(3.19)	(0.96)	(2.64)	(3.64)
Low × High	0.0131	-0.0204*	-0.0555***	0.0299**	-0.0035	-0.0361**
	(0.87)	(1.83)	(3.40)	(2.11)	(0.33)	(2.23)
High × Low	-0.0397***	0.0413***	-0.0018	-0.0456***	0.0236**	-0.0060
	(2.58)	(3.64)	(0.12)	(3.16)	(2.15)	(0.38)
High × High	0.0323**	0.0822***	0.0688***	0.0320**	0.0824***	0.0708***
	(2.34)	(7.36)	(4.11)	(2.47)	(7.63)	(4.26)
Difference between High × High and Low × Low						
	0.0173	0.0971***	0.1205***	0.0197	0.1103***	0.1292***
	(0.97)	(6.66)	(5.56)	(1.18)	(7.83)	(6.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Mandate	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.045	0.074	0.154	0.041	0.078	0.152
N	193,996	282,851	193,995	193,996	282,851	193,995

Panel B: Active Share (broad-based benchmarks) × Prior Performance

	CAPM			FFC4		
	United States	Europe	Asia-Pacific	United States	Europe	Asia-Pacific
Low × Low	-0.0377*	-0.0670***	-0.0778***	-0.0233	-0.0635***	-0.0762***
	(1.81)	(4.35)	(3.81)	(1.32)	(4.89)	(4.13)
Low × High	0.0447	0.0381**	0.0323	0.0345	0.0497***	0.0035
	(1.43)	(2.21)	(1.30)	(1.39)	(3.27)	(0.15)
High × Low	-0.0409	-0.0391	-0.0333	-0.0212	-0.0419**	-0.0459*
	(1.03)	(1.48)	(1.16)	(0.81)	(1.99)	(1.78)
High × High	0.0119	0.1542***	0.1422***	-0.0135	0.1552***	0.1324***
	(0.36)	(5.99)	(4.96)	(0.58)	(7.52)	(5.16)
Difference between High × High and Low × Low						
	0.0496	0.2212***	0.2200***	0.0098	0.2187***	0.2085***
	(1.15)	(6.93)	(5.98)	(0.30)	(8.17)	(6.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Mandate	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.047	0.075	0.156	0.041	0.079	0.155
N	174,205	255,290	170,270	174,205	255,290	170,270

Appendix 1: Data

Our primary source of fund characteristics (for non-U.S.-sold funds) and portfolio holdings (all funds) is Morningstar Direct. Morningstar is widely used in mutual fund studies (e.g., Berk and van Binsbergen (2015), Pastor, Stambaugh, and Taylor (2015), Broman et al. (2023), and Jagannathan, Jiao, and Karolyi (2022)).

We identify global equity funds based on the Morningstar Category variable. The category names vary by region of sale. They are i) United States—foreign large blend, foreign large value, foreign large growth, foreign small/mid blend, foreign small/mid value, foreign small/mid growth, world large stock and world small/mid stock; ii) Europe—global large-cap blend, global large-cap growth, global large-cap value, global small/mid-cap, global equity income, and global flex-cap; iii) Canada—global equity, global small/mid-cap equity and international equity; and iv) Australia—world large value, world large growth, world large blend, and world small/mid/small. This step automatically excludes other investment mandates, including single-country, regional and global emerging markets funds; as well as other "specialty funds", such sector funds, balanced funds, and alternative strategy funds (e.g., long-short).

We also use portfolio holdings data to remove incorrectly labelled funds. Specifically, funds that invest more than 80% in a single region or country (average over the prior two years) are labelled instead as regional/country funds, and are therefore removed from the sample.

We also remove index funds, lifecycle funds, fund-of-funds, as identified by the corresponding indicator variables in Morningstar. While the standard practice in the literature is to exclude fund-of-fund structures, we go a step further by also removing feeder funds given their equivalence to funds of funds and to avoid duplication. A master-feeder structure is characterized by a series of (open-end) feeder funds that invest their assets in a single master portfolio, which may follow a different regulatory structure (e.g., insurance product). Feeder funds typically have missing holdings data. Additional details are provided by Broman and Lovelace (2024).

We further drop funds domiciled in Hong Kong, Israel, Japan, New Zealand, Singapore, and South Korea because of missing time-series data on fees (Hong Kong, Israel, and Japan), holdings data is reported at most semi-annually (Hong Kong, Japan and Singapore), and/or low coverage of funds especially after removing feeder funds (Japan and South Korea). We also exclude island offshore locations, such as the Cayman Islands, since the regulatory structure may be more permissive than those used elsewhere. Our final sample of domiciles includes North America (U.S. and Canada), developed Europe (including Ireland/Luxembourg), and Australia.

For U.S.-sold funds, we use the CRSP MFDB as is standard practice in the literature. We link Morningstar and CRSP MFDB 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. Following the procedures in Berk and van Binsbergen (2015) and Pastor, Stambaugh, and Taylor (2015), we reconcile the U.S. data on fund returns between Morningstar Direct and CRSP MFDB, though the incidence of such errors is exceedingly rare during our (more recent) sample period. Additional details on the matching between the two databases are provided by Broman, Densmore and Shum-Nolan (2023).

Appendix 2: Variable Construction

Active share is based on Cremers and Petajisto (2009) and is defined as follows:

$$\text{ACTIVE\_SHARE}_{i,t} = 0.5 \times \sum_{j=1}^{N} \left(w_{i,j,t} - w_{j,t}^{BMK}\right) \qquad (A1)$$

where $w_{i,j,t}$ = weight invested by fund i in security j at quarter-end t; and $w_{j,t}^{BMK}$ is the weight of security j in the benchmark index (BMK).

Next, we describe in greater detail how benchmark index funds are assigned for our sample:

Index fund	Market	Ticker	Inception
Vanguard Total International Stock Index Fund	DM + EM ex US	VGTSX	04/29/1996
Vanguard Developed Markets Index Fund	DM ex US	VTMGX	08/17/1999
Vanguard Total World Stock ETF [Post 2008]	DM + EM	VT	06/24/2008
Vanguard Total World Stock ETF [Pre 2008]			
Vanguard Total Stock Market Index Fund	USA	VTSMX	04/27/1992
Vanguard Emerging Markets Stock Index Fund	EM	VEIEX	4/5/1994
Vanguard European Stock Index Fund	Europe	VESIX	05/15/2000
Vanguard Pacific Stock Index Fund	Asia-Pacific	VPKIX	05/15/2000

Starting with the universe of global/global ex-U.S. equity funds as identified by the Morningstar Category variable, we start by assigning them into four categories: i) All Countries (DM + EM), ii) Developed Countries only (DM), iii) All countries excluding USA (DM+EM ex US), and iv) Developed countries excluding USA (DM ex USA). Thus, Global equity funds are either i) or ii); while Global ex-US equity funds are either iii) or iv). For conciseness, we occasionally refer to index funds by their abbreviated name (based on the column (2) in the table above).

Outside of North America, Morningstar does not actually differentiate between global and global ex-U.S. equity funds. To ensure a consistent classification across the world, we reclassify non-U.S.-sold global equity funds as global ex-U.S. if the fund holds less than 15% of its assets in U.S. equities over the prior two years on average. The 15% cut-off aligns with how Morningstar classifies global ex-U.S. in the United States and Canada (according to the manual for the

Morningstar Category variable). Empirically, we observe that about 1% (0%) of Canadian (U.S.) global ex-US equity funds have U.S. allocations in excess of 15%.

To determine emerging market status (i.e., DM vs DM+EM; or DM ex US vs. DM+EM ex-US), we calculate the average allocation to EM stocks over the prior two years. If the allocation is greater than half of that for the corresponding benchmark index with EM stocks (e.g., Vanguards Total Stock Market Index Fund for Global ex-U.S. equity or Vanguard World Stock index for Global equity), then we assign the fund a DM+EM status. Otherwise, it is assigned a DM only status. Since Vanguard does not offer a DM only index fund, we create one ourselves based on Vanguard World Stock index by excluding all EM stocks. The vast majority of global funds are classified as developed markets only: 24.4% are DM ex-US; 59% are DM, 6.3% are DM+EM ex USA and 10.3% are DM+EM.

The Vanguard World Stock index fund is only available after July 2008. Prior to this date, we construct the index using three constituent funds that cover developed markets (Vanguard Developed Markets Index Fund), emerging markets (Vanguard Emerging Markets Stock Index Fund) and the U.S. equity markets (Vanguards Total Stock Market Index Fund). To combine the three funds into one global benchmark, we start by computing the weights in July 2008 based on Vanguard Total World Stock Index Fund. We then back-fill the weights by assuming that any changes over time are solely driven by return differences.

We construct *anomaly tilts* at the fund-quarter level based on the extent to which a portfolio is tilted towards several well-known asset pricing anomalies (from Stambaugh et al. (2012)), following Avramov et al. (2020). The original study includes 11 anomalies in nine categories. To minimize overlaps, we keep one anomaly from each category as advocated by Gao and Wang (2023), including total accruals, asset growth, gross profitability, investment-to-assets, momentum, net operating assets, Ohlson's O-score, and return on assets. In contrast to Avramov et al. (2020), we drop the equity issuance anomaly because it is not well defined for global funds that hold stocks from non-Anglo-Saxon countries where secondary equity issuances are extremely rare.[14]

For each anomaly characteristic, Avramov et al. (2020) calculate percentile scores (ranging from 0 to 1) using the entire universe of stocks, which includes hard-to-trade micro-caps that account for 40-60% of all stocks by region. However, mutual funds generally tilt towards larger securities and do not invest meaningfully in micro-cap stocks in the first place (e.g., Bhattacharya, and Galpin (2011)).[15] To remedy this, we follow the conventional practice in the asset pricing literature of computing breakpoints based on non-micro-caps. For the U.S., we define non-micro-caps as those above the 20th percentile on NYSE market cap; for non-U.S. markets, we include stocks that cumulatively account for 99% of the total market cap by region following Dyakov, Jiang, and Verbeek (2020). The breakpoints are computed separately by region (e.g., Fama and French (2017))—United States, North America (for Canada only), Developed Europe, Emerging Europe, Developed Asia-Pacific ex-Japan, Japan, Emerging Asia-Pacific, and Latin America. We then compute decile scores for each stock j on a particular characteristic C at the end of June of each year, with higher numbers indicating *greater* anomaly tilts, and higher expected returns.[16] These scores are then aggregated to the fund-level by taking the portfolio-weighted average of the stocks held by the fund. Finally, we subtract the corresponding value-weighted characteristic score of the benchmark:

[14] As a case in point, about 80% of Japanese non-micro-cap stocks have zero equity issuance. The corresponding fractions are far in excess of 50% for most non-Anglo-Saxon countries. Since we use regional breakpoints to calculate characteristic decile scores, we would inadvertently classify most non-Anglo-Saxon stocks as having low net equity issuance, and the majority of Anglo-Saxon stocks as having high net equity issuance.
[15] For global/global ex-U.S. equity funds, there is not even a small-cap category, only SMID (or small + mid-cap)
[16] Avramov et al. (2020) sign the measure in the opposite way refer to it as stock overpricing.

$$C_{i,t} = \sum_{j=1}^{J} \left(w_{i,j,t} - w_{j,t}^{BMK}\right) C_{j,t} \qquad \text{(A2)}$$

where $w_{i,j,t}$ is the weight of stock *j* in the portfolio of fund *i* at time *t,* and $w_{j,t}^{BMK}$ is the weight of stock *b* in the benchmark. Finally, we take an equal-weighted average of Eq. (1) across the eight anomalies, and we refer to it as the *Anomaly Tilt*. As a proxy for the benchmark, we use the index fund that best matches the fund's investment universe. We use the same benchmark index funds (by Vanguard) that we used for the calculation of active share (as outlined above).

Variation in the Value of Active Share Across Regions of Investments: Evidence from Global Equity Funds

Internet Appendix

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

IA. 1 Defining style benchmarks

To select the style benchmark for each fund, we first group each fund into one of four broad categories: i) All Country World Index (MSCI ACWI) (developed and emerging markets), ii) MSCI WORLD (developed markets), iii) MSCI ACWI ex. U.S., or iv) MSCI WORLD ex. U.S.. The geographical investment mandate (global or global ex-U.S.), size (large or mid/small) and style tilt is based on the Morningstar Category variable, which is available monthly. Outside of the U.S., Morningstar does not differentiate between global and global ex-U.S. equity. We reclassify non-U.S.-sold global equity funds as global ex-U.S. if the fund hold less than 12.5% of its assets in U.S. equities on average over the prior two years. The 12.5% cut-off corresponds to the 92nd (3rd) percentile for the weight in U.S. stocks by global ex-U.S. (global equity) funds sold in the United States. We therefore have four style benchmarks (large-value; large-blend; large-growth; small/mid) and four investment mandates (DM; DM ex USA; DM+EM; DM+EM ex USA). In total, we have 16 (4 × 4) style benchmarks corresponding to 16 MSCI indices. Their returns are used in the fund-level performance analysis.

Table IA-1: Return Predictability of Active Share by Region of Sale

This table reports the results for pooled OLS regressions of fund performance on quintile dummies for active share (broad-based benchmarks), for global equity funds only. We split the sample further by Region of Sale (ROS = North America, Europe, or Australia). Controls variables (omitted for brevity) include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

	CAPM alpha			FFC4 alpha		
Quintiles	ROS = NA	ROS = EU	ROS = AUS	ROS = NA	ROS = EU	ROS = AUS
Q2	0.0135	0.0303*	-0.0055	-0.0129	0.0192	-0.0126
	(0.62)	(1.75)	(0.11)	(0.63)	(1.15)	(0.26)
Q3	0.0226	0.0542**	0.0455	0.0163	0.0331*	-0.0126
	(0.93)	(2.57)	(0.75)	(0.74)	(1.65)	(0.22)
Q4	0.0387	0.0594**	0.1465**	0.0423	0.0449*	0.1268**
	(1.27)	(2.25)	(2.26)	(1.58)	(1.91)	(2.18)
Q5	0.0382	0.0603	0.1773**	0.0300	0.0633*	0.1409*
	(1.01)	(1.47)	(2.27)	(0.86)	(1.93)	(1.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.074	0.084	0.074	0.084	0.086	0.093
N	52,435	147,615	9,822	52,435	147,615	9,822

	FF6 alpha			Bmk.-adj. alpha		
Quintiles	ROS = NA	ROS = EU	ROS = AUS	ROS = NA	ROS = EU	ROS = AUS
Q2	-0.0134	0.0087	-0.0360	0.0139	0.0147	-0.0040
	(0.63)	(0.50)	(0.68)	(0.57)	(0.81)	(0.08)
Q3	0.0359	0.0277	-0.0290	0.0095	0.0412*	0.0274
	(1.44)	(1.37)	(0.46)	(0.35)	(1.84)	(0.42)
Q4	0.0639**	0.0382	0.1480**	0.0266	0.0653**	0.1262*
	(2.06)	(1.57)	(2.33)	(0.78)	(2.58)	(1.86)
Q5	0.0479	0.0570*	0.1573**	0.0130	0.0817**	0.1368**
	(1.25)	(1.65)	(2.06)	(0.33)	(2.20)	(2.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.128	0.110	0.149	0.136	0.141	0.142
N	52,435	147,615	9,822	53,065	149,043	10,188

Table IA-2: Characteristic Timing

This table reports the results for pooled OLS regressions of characteristic timing (by Daniel et al. (1997)) on quintile dummies for active share (broad-based). We extend Daniel et al. (1997) to international markets following Dyakov, Jiang, and Verbeek (2020) and Broman, Densmore and Shum (2023). The DGTW characteristic timing measure captures market timing broadly speaking (including style timing). It is defined as the product of the fund's portfolio weight in *t*-1 and the current benchmark return minus the product of the fund's portfolio weight at *t*-13 and the current benchmark return that is matched as of *t*-13, summed across all holdings. The original DGTW methodology uses 5×5×5 benchmarks based on size, value, and momentum. To account for the asset growth and profitability factors, we extend the DGTW approach to include these two factors. To maintain diversification, we cut the number of benchmark portfolios to 2 (size) ×3 (B/M) × 3 (Mom) × 3 (AG) × 3 (Prof) = 162. Controls variables (omitted for brevity) include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

	Characteristic Timing (Original)		Characteristic Timing (Extended)	
Quintiles	Global ex-U.S.	Global	Global ex-U.S.	Global
Q2	-0.0028	0.0033	-0.0017	0.0041
	(0.43)	(0.55)	(0.22)	(0.55)
Q3	0.0043	-0.0055	0.0096	-0.0075
	(0.50)	(0.70)	(1.00)	(0.78)
Q4	0.0095	-0.0042	-0.0048	-0.0132
	(0.79)	(0.40)	(0.34)	(1.08)
Q5	0.0326**	0.0138	-0.0080	0.0148
	(2.04)	(0.87)	(0.43)	(0.83)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Style	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Adjusted R^2	0.076	0.081	0.106	0.090
N	91,594	197,299	91,594	197,299

Table IA-3: Decomposing the Return Predictability at the Regional Sub-Portfolio Level

This table reports the results for regressions of regional sub-portfolio risk-adjusted performance on quintile dummies for regional active share (broad-based benchmarks) and control variables. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe, and iii) Asia-Pacific. Sub-samples results are presented by Region of Sale (ROS). Control variables are the same as in Table 3, including fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: U.S. sub-portfolio [Global equity funds only]

	CAPM			FFC4		
AS quintile	ROS = NA	ROS = EU	ROS = AUS	ROS = NA	ROS = EU	ROS = AUS
Q2	-0.0219	0.0021	-0.0832	-0.0229	0.0001	-0.0406
	(0.70)	(0.14)	(1.51)	(0.80)	(0.00)	(0.80)
Q3	0.0245	-0.0091	-0.0816	0.0144	-0.0110	-0.0196
	(0.77)	(0.57)	(1.52)	(0.49)	(0.72)	(0.40)
Q4	-0.0199	-0.0221	0.0102	-0.0249	-0.0318**	0.0465
	(0.61)	(1.34)	(0.18)	(0.83)	(2.03)	(0.87)
Q5	0.0030	-0.0426**	0.0795	-0.0040	-0.0286	0.0395
	(0.08)	(2.29)	(1.29)	(0.12)	(1.62)	(0.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.051	0.049	0.048	0.055	0.041	0.057
N	48,693	135,556	9,740	48,693	135,556	9,740

Panel B: Europe sub-portfolio [Global equity funds only]

	CAPM			FFC4		
AS quintile	ROS = NA	ROS = EU	ROS = AUS	ROS = NA	ROS = EU	ROS = AUS
Q2	0.0038	0.0178	0.0246	0.0204	-0.0082	-0.0037
	(0.12)	(1.20)	(0.50)	(0.64)	(0.56)	(0.08)
Q3	-0.0043	0.0166	-0.0313	0.0201	-0.0072	0.0054
	(0.14)	(1.08)	(0.57)	(0.65)	(0.48)	(0.10)
Q4	0.0484	0.0657***	-0.0139	0.0637**	0.0394**	-0.0504
	(1.54)	(4.15)	(0.24)	(2.05)	(2.55)	(0.88)
Q5	0.0982***	0.1403***	0.0568	0.0942***	0.1039***	0.0459
	(2.91)	(7.44)	(0.83)	(2.83)	(5.64)	(0.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.099	0.075	0.097	0.096	0.075	0.098
N	44,343	132,791	9,077	44,343	132,791	9,077

Panel C: Asia-Pacific [Global equity funds only]						
	CAPM			FFC4		
AS quintile	ROS = NA	ROS = EU	ROS = AUS	ROS = NA	ROS = EU	ROS = AUS
Q2	0.0589	0.0671***	0.0178	0.0413	0.0502**	0.0369
	(1.21)	(2.75)	(0.24)	(0.84)	(2.06)	(0.51)
Q3	0.0861*	0.0814***	0.0804	0.0714	0.0565**	0.0697
	(1.82)	(3.22)	(1.07)	(1.50)	(2.24)	(0.95)
Q4	0.0371	0.1049***	0.0849	0.0520	0.0837***	0.0477
	(0.78)	(4.11)	(1.03)	(1.08)	(3.28)	(0.59)
Q5	0.1102**	0.0867***	0.0870	0.1045**	0.0629**	0.0840
	(2.11)	(2.90)	(0.86)	(1.98)	(2.11)	(0.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.177	0.139	0.143	0.172	0.135	0.145
N	28,368	72,370	6,134	28,368	72,370	6,134

Table IA-4: Regional Active Share and Anomaly Tilts by Region of Sale

This table reports the results for regressions of sub-portfolio risk-adjusted performance on active share (broad-based) interacted with anomaly tilts for the sub-sample of global equity funds. We discretize active share and its interactions by using the top (*High*) and bottom (*Low*) tercile. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe, and iii) Asia-Pacific. Each of the three panels presents results for one sub-portfolio. Results are estimated separately by Region of Sale (ROS). Control variables are the same as in Table 3 and include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: US Sub-portfolio

	CAPM alpha			FFC4 alpha		
	ROS: All	ROS = NA	ROS = EU	ROS: All	ROS = NA	ROS = EU
AS × Anomaly	(1)	(2)	(3)	(4)	(5)	(6)
Low × Low	-0.0456***	0.0033	-0.0664***	-0.0195	0.0048	-0.0352*
	(2.83)	(0.10)	(3.32)	(1.28)	(0.16)	(1.86)
Low × High	0.0577***	0.0024	0.0632***	0.0518***	0.0188	0.0573***
	(4.31)	(0.07)	(4.17)	(4.11)	(0.60)	(3.98)
High × Low	-0.0603***	-0.0732***	-0.0700***	-0.0359***	-0.0185	-0.0516***
	(4.81)	(2.88)	(4.63)	(3.04)	(0.78)	(3.59)
High × High	0.0681***	0.0865***	0.0607***	0.0561***	0.0642**	0.0561***
	(4.63)	(2.80)	(3.55)	(4.04)	(2.23)	(3.45)
Difference between High × High and Low × Low						
	0.1137***	0.0832**	0.1271***	0.0756***	0.0594	0.0913***
	(5.54)	(2.01)	(5.10)	(3.90)	(1.54)	(3.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.046	0.049	0.038	0.043	0.041
N	193,562	48,259	135,556	193,562	48,259	135,556

Panel B: Europe sub-portfolio

	CAPM alpha			FFC4 alpha		
	ROS = All	ROS = NA	ROS = EU	ROS = All	ROS = NA	ROS = EU
AS × Anomaly	(2)	(3)	(4)	(6)	(7)	(8)
Low × Low	-0.0602***	-0.0171	-0.0707***	-0.0319**	-0.0479	-0.0348**
	(4.13)	(0.46)	(4.25)	(2.24)	(1.31)	(2.14)
Low × High	0.0265*	0.0533	0.0144	0.0137	0.0201	0.0067
	(1.94)	(1.62)	(0.90)	(1.02)	(0.62)	(0.43)
High × Low	-0.0276**	-0.0244	-0.0269*	-0.0075	-0.0044	-0.0037
	(2.15)	(0.93)	(1.76)	(0.60)	(0.17)	(0.25)
High × High	0.1632***	0.1746***	0.1524***	0.1246***	0.1349***	0.1188***
	(12.22)	(7.05)	(9.20)	(9.52)	(5.51)	(7.33)
Difference between High × High and Low × Low						
	0.2232***	0.1917***	0.2231***	0.1565***	0.1828***	0.1535***
	(12.11)	(4.56)	(10.16)	(8.66)	(4.41)	(7.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.079	0.099	0.076	0.078	0.094	0.075
N	186,076	44,201	132,791	186,076	44,201	132,791

Panel C: Asia-Pacific sub-portfolio

	CAPM alpha			FFC4 alpha		
	ROS = All	ROS = NA	ROS = EU	ROS = All	ROS = NA	ROS = EU
AS × Anomaly	(2)	(3)	(4)	(6)	(7)	(8)
Low × Low	-0.1331***	-0.1632***	-0.1216***	-0.1082***	-0.1453***	-0.0999***
	(6.59)	(3.02)	(5.27)	(5.35)	(2.67)	(4.34)
Low × High	0.0171	-0.0354	0.0367	0.0106	-0.0608	0.0349
	(0.66)	(0.69)	(1.15)	(0.41)	(1.18)	(1.10)
High × Low	-0.1167***	-0.0950**	-0.1327***	-0.0981***	-0.0780*	-0.1089***
	(5.12)	(2.18)	(4.77)	(4.31)	(1.78)	(3.92)
High × High	0.0840***	0.0802**	0.0808***	0.0967***	0.1217***	0.0758***
	(4.26)	(2.19)	(3.30)	(4.90)	(3.30)	(3.10)
Difference between High × High and Low × Low						
	0.2171***	0.2434***	0.2024***	0.2048***	0.2670***	0.1757***
	(8.34)	(3.96)	(6.55)	(7.87)	(4.31)	(5.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.147	0.178	0.140	0.142	0.172	0.135
N	106,840	28,331	72,370	106,840	28,331	72,370

Table IA-5: Regional Active Share (Style Peers) and Anomaly Tilts

This table reports the results for regressions of sub-portfolio risk-adjusted performance on active share (*style peers*) interacted with anomaly tilts. We discretize active share and its interactions by using the top (*High*) and bottom (*Low*) tercile. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe, and iii) Asia-Pacific. Each of the three panels presents results for one sub-portfolio. Results are estimated separately by region of sale (ROS), and by global/global ex-U.S. equity (only in Panels B and C). Control variables are the same as in Table 3 and include fund age, AUM, family AUM, net fund flow over the prior 12 months, the annual net expense ratio, and tracking error. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: CAPM alpha

	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0459***	-0.0809***	-0.0516**	-0.1114***	-0.0953***
	(2.91)	(3.89)	(2.21)	(3.75)	(3.61)
Low × High	0.0739***	0.0443**	0.0363*	0.0612*	0.0186
	(5.53)	(2.32)	(1.73)	(1.76)	(0.57)
High × Low	-0.0819***	-0.0458	-0.0071	-0.1416***	-0.1400***
	(6.49)	(1.56)	(0.22)	(3.72)	(3.71)
High × High	0.0376**	0.1289***	0.1417***	0.0773**	0.1212***
	(2.54)	(5.12)	(5.07)	(2.34)	(3.55)
Difference between High × High and Low × Low					
	0.0835***	0.2098***	0.1933***	0.1887***	0.2164***
	(4.09)	(5.92)	(5.19)	(3.97)	(5.06)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.044	0.080	0.092	0.149	0.177
N	191,952	184,451	89,683	105,537	82,801

Panel B: FFC4 alpha

	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0182	-0.0466**	0.0009	-0.1136***	-0.0985***
	(1.22)	(2.54)	(0.04)	(4.06)	(4.06)
Low × High	0.0416***	0.0372**	-0.0059	0.0724**	0.0123
	(3.30)	(2.05)	(0.33)	(2.14)	(0.38)
High × Low	-0.0444***	-0.0188	0.0435	-0.1205***	-0.1511***
	(3.73)	(0.73)	(1.57)	(3.35)	(4.44)
High × High	0.0295**	0.1022***	0.1309***	0.0740**	0.1071***
	(2.10)	(4.37)	(4.86)	(2.38)	(3.48)
Difference between High × High and Low × Low					
	0.0477**	0.1488***	0.1300***	0.1876***	0.2056***
	(2.47)	(4.64)	(3.74)	(4.41)	(5.31)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.038	0.078	0.099	0.143	0.177
N	191,952	184,451	89,683	105,537	82,801

Panel C: FF6 alpha					
	U.S. subp.	Europe sub-portfolio		Asia-Pacific sub-portfolio.	
	Global	Global	Global ex-U.S.	Global	Global ex-U.S.
AS × Anomaly tilt	(1)	(2)	(3)	(4)	(5)
Low × Low	-0.0226	-0.0314	0.0047	-0.1195***	-0.0865***
	(1.50)	(1.56)	(0.22)	(3.85)	(3.31)
Low × High	0.0439***	0.0193	-0.0231	0.0685*	0.0045
	(3.43)	(1.01)	(1.31)	(1.83)	(0.13)
High × Low	-0.0546***	-0.0181	0.0250	-0.0836**	-0.1374***
	(4.52)	(0.67)	(0.86)	(2.18)	(3.80)
High × High	0.0089	0.0635***	0.1293***	0.0431	0.0722**
	(0.63)	(2.72)	(4.69)	(1.32)	(2.30)
Difference between High × High and Low × Low					
	0.0315	0.0950***	0.1246***	0.1626***	0.1586***
	(1.62)	(2.87)	(3.47)	(3.52)	(3.90)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Style	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.038	0.073	0.107	0.273	0.311
N	191,952	184,451	89,683	105,537	82,801

Table IA-6: Active Share and Anomaly Tilts: Fund-level for Global Equity Funds

This table reports the results for pooled OLS regressions of fund performance on lagged measures of active share (broad-based) interacted with anomaly tilts for the sub-sample of global equity funds. Results are presented separately by Region of Sale (ROS)—North America and Europe. All specifications include style, mandate and calendar time fixed effects. Controls variables (omitted for brevity) are the same as in Table 3. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Active Share ×	CAPM		FFC4		FF6	
Anomaly Tilt	ROS = NA	ROS = EU	ROS = NA	ROS = EU	ROS = NA	ROS = EU
Low × Low	-0.0350	-0.0726***	-0.0298	-0.0452***	-0.0494**	-0.0436**
	(1.36)	(3.76)	(1.35)	(2.62)	(2.05)	(2.53)
Low × High	0.0173	0.0231	0.0042	0.0141	-0.0255	0.0098
	(0.72)	(1.17)	(0.19)	(0.78)	(1.03)	(0.52)
High × Low	-0.0514	-0.0495	0.0062	-0.0098	-0.0044	0.0034
	(1.64)	(1.58)	(0.22)	(0.45)	(0.14)	(0.14)
High × High	0.0984***	0.0997***	0.0669**	0.0778***	0.0536	0.0676***
	(3.08)	(3.99)	(2.08)	(3.42)	(1.50)	(2.87)
Difference between High × High and Low × Low						
	0.1334***	0.1722***	0.0966**	0.1231***	0.1030***	0.1112**
	(3.30)	(5.16)	(2.45)	(4.10)	(2.42)	(3.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.072	0.082	0.082	0.084	0.124	0.105
N	55,254	162,516	55,254	162,516	55,254	162,516

Table IA-7: Active Share (Style Peers) and Anomaly Tilts: Fund-level Results

This table reports the results for pooled OLS regressions of fund performance on lagged measures of Active Share (Style Peers) interacted with anomaly tilts and control variables. Results are presented separately by investment mandate. All specifications include style, mandate and calendar time fixed effects. Controls variables (omitted for brevity) are the same as in Table 3. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Active Share ×	CAPM alpha		FFC4		FF6	
Anomaly Tilt	Global	Global ex-US	Global	Global ex-US	Global	Global ex-US
Low × Low	-0.0377*	-0.0670***	-0.0778***	-0.0233	-0.0635***	-0.0762***
	(1.81)	(4.35)	(3.81)	(1.32)	(4.89)	(4.13)
Low × High	0.0447	0.0381**	0.0323	0.0345	0.0497***	0.0035
	(1.43)	(2.21)	(1.30)	(1.39)	(3.27)	(0.15)
High × Low	-0.0409	-0.0391	-0.0333	-0.0212	-0.0419**	-0.0459*
	(1.03)	(1.48)	(1.16)	(0.81)	(1.99)	(1.78)
High × High	0.0119	0.1542***	0.1422***	-0.0135	0.1552***	0.1324***
	(0.36)	(5.99)	(4.96)	(0.58)	(7.52)	(5.16)
Difference between High × High and Low × Low						
	0.1554***	0.2647***	0.1119***	0.1530***	0.1093***	0.1053***
	(5.50)	(6.20)	(4.21)	(4.52)	(3.96)	(3.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Style	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.047	0.075	0.156	0.041	0.079	0.155
N	174,205	255,290	170,270	174,205	255,290	170,270

Table IA-8: Determinants of Regional Sub-Portfolio Active Share [Style Peer]

In Panel A, we report the results for pooled OLS regressions of regional sub-portfolio active share [style peers] on regional anomaly tilts. For each fund *i* and month *t*, there are three observations for mutually exclusive regional sub-portfolios: i) United States, ii) Europe (EU), and iii) Asia-Pacific (ASPA). Sub-samples results are presented by Region of Sale (ROS). Active share and anomaly tilts are both measured at the regional sub-portfolio level. In Panel B, we instead estimate regressions of fund-level active share on the fund's regional sub-portfolio anomaly tilts (US, EU and Asia-Pacific). In both Panels, the control variables are the same and include fund age, AUM, family AUM, net fund flow over the prior 12 months, the tracking error, the annual net expense ratio, and tracking error. All specifications include style and time fixed effects. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund and style × time (*t*-statistics in brackets).

Panel A: Y = Regional Sub-portfolio Active Share [Style Peer]

	Global ex-U.S.	Global equity		
	ROS = All	ROS = All	ROS = NA	ROS = EU
Variables	(1)	(2)	(3)	(4)
Anomaly Tilt × US		-1.421***	-0.825***	-1.381***
		(9.81)	(3.28)	(8.43)
Anomaly Tilt × EU	0.253	-0.087	0.350	-0.188
	(1.30)	(0.69)	(1.37)	(1.44)
Anomaly Tilt × ASPA	0.454**	0.285	-1.185***	0.735***
	(2.33)	(1.51)	(3.90)	(3.65)
US dummy		-3.878***	-4.177***	-4.016***
		(19.87)	(13.38)	(17.13)
ASPA dummy	4.903***	2.490***	0.724*	3.088***
	(19.91)	(10.36)	(1.96)	(10.85)
ln(Age)	0.541**	-0.462**	0.285	-0.402*
	(1.98)	(2.30)	(0.67)	(1.81)
ln(AUM)	-3.001***	-2.473***	-3.443***	-2.233***
	(9.18)	(7.99)	(4.66)	(8.36)
ln(FAMILY AUM)	-1.354***	-0.434**	-1.411***	-0.368
	(4.62)	(2.07)	(3.47)	(1.53)
Exp. Ratio	0.639**	1.261***	0.831***	0.602**
	(2.13)	(5.54)	(2.66)	(2.20)
Net Flow	0.559***	0.273**	0.429**	0.228*
	(3.97)	(2.53)	(1.97)	(1.94)
Track. Err	4.238***	2.930***	3.251***	3.450***
	(14.71)	(11.70)	(8.33)	(14.10)
Fixed effects				
Style	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Adjusted R2	0.450	0.286	0.376	0.300
N	171,890	479,465	117,250	339,361

Panel B: Y = Fund-level Active Share [Style Peer]				
	Global ex-U.S.		Global Equity funds	
Variables	(1)	(2)	(3)	(4)
Anomaly tilt	0.8576***		-0.4811***	
	(4.11)		(3.78)	
Anomaly tilt (US subp.)				-1.4095***
				(7.38)
Anomaly tilt (EU subp.)		-0.2536		0.0505
		(1.45)		(0.32)
Anomaly tilt (ASPA subp.)		1.0168***		1.4768***
		(5.24)		(6.76)
ln(Age)	0.6222**	0.5486*	-0.6384***	-0.3058
	(2.08)	(1.81)	(3.06)	(1.02)
ln(AUM)	-3.4326***	-3.3631***	-2.1442***	-2.7148***
	(10.17)	(9.78)	(8.22)	(7.27)
ln(FAMILY AUM)	-0.9548***	-1.1099***	-0.5571***	-0.4857
	(3.51)	(3.71)	(2.83)	(1.48)
Exp. Ratio	0.2738	0.3134	1.3859***	1.4463***
	(0.96)	(1.03)	(6.44)	(4.44)
Net Flow	0.4778***	0.5307***	0.2489**	0.1395
	(3.53)	(3.57)	(2.42)	(0.84)
Track. Err	4.0441***	4.1679***	3.5579***	3.5439***
	(13.96)	(13.11)	(14.48)	(8.16)
Fixed effects				
Style	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Adjusted R2	0.431	0.446	0.322	0.315
N	97,575	85,995	207,863	106,994