Global Fund Flows: What They Reveal About Global Factors

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This draft: May 2024

Abstract

Using novel data on global asset managers, this study investigates the asset pricing factors that guide global fund flows. Among the prominent models assessed, the Capital Asset Pricing Model (CAPM) emerges as the most influential in predicting global fund flows. These results are primarily driven by institutional investors, rather than high-net-worth individuals, although all investor types do not seem to use sophisticated benchmarks. The prevalent use of the CAPM leads to correlated demand, which positively predicts stock returns in the short term but reverses in the long term. Our findings suggest that the CAPM remains an important model after all.

JEL Classification: G11, G12, G23

Keywords: global fund flows, asset pricing factors, investor sophistication, flow-induced trading

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1 Introduction

Global equity investors delegate at least \$3.3 trillion per year to active asset management over the period from 2003 through 2023, according to Nasdaq eVestment data.[1] These investors, domiciled in 58 countries/regions, have direct access to global asset managers and can actively move capital across borders. In a given year during the same period, they allocate at least \$46 billion of net capital (inflows minus outflows) to active global mandates. Considering the size and potential impacts of these activities, understanding which risk factors these global investors use in their capital allocation decisions is imperative. It provides insights into the relevance of asset pricing risk factors in the global market. To the extent that capital flows ultimately influence asset prices (Lou, 2012), the answer to this question also has broader implications for international capital budgeting in which an appropriate asset pricing model for calculating the cost of capital is required.

The extant literature has shown that net fund flows are influenced by funds' past performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998a; Del Guercio and Tkac, 2002). However, perhaps due to the proliferation of asset pricing factors over the past decades (Harvey, Liu, and Zhu, 2016), researchers have only recently considered using mutual fund flows as a testing ground to examine which risk factors matter to investors.[2] Two pivotal studies in this debate, Barber, Huang, and Odean (2016) and Berk and Van Binsbergen (2016), compare various prominent asset pricing models and find that U.S. mutual fund flows exhibit the highest correlation with alphas estimated using the Capital Asset Pricing Model (CAPM). While other studies also reach a similar conclusion (e.g., Blocher and Molyboga, 2017; Agarwal, Green, and Ren, 2018), Jegadeesh and Mangipudi (2021) show that the four-factor model (i.e., the Fama and French's (1993) three factors and Carhart's (1997) momentum factor) wins the horse race, because its alphas are estimated with the least noise. In contrast to these studies,

[1]These statistics pertain to global asset managers (excluding ETFs) tasked with employing active investing strategies to invest globally and catering to global investors (excluding, for example, a UK-based global fund that only serves UK domestic investors even though the fund also has a global mandate). Nasdaq eVestment is a prominent data analytics provider in the global asset management industry.

[2]It is useful to note that tests using fund lows do not reveal the *true* asset pricing model, which empiricists do not observe. Rather, the goal is exploratory, i.e., to determine which factors matter to fund investors in reality. We remain agnostic regarding which asset pricing model is a true model.

Del Guercio and Tkac (2008), Evans and Sun (2021) and Ben-David, Li, Rossi, and Song (2022b) find that U.S. mutual fund flows follow Morningstar ratings rather than any risk factors, suggesting that these mutual fund investors are not sophisticated.

How investors use an asset pricing factor in their capital allocation decision depends on their perception of the factor as risk or mispricing. If investors treat a factor as risk, they will discount a fund's performance based on its exposure to the factor. On the other hand, if they perceive a factor as mispricing (alpha opportunities), their flows will be positively correlated with fund returns traced to that factor. It is thus useful to view the debate on the sensitivity of fund flows to an asset pricing factor within the broader debate in the asset pricing literature. Arguably, with the exception of market beta risk, many of the risk factors incorporated into contemporary asset pricing models are empirically motivated from stylized patterns in returns. As such, the literature has not reached a consensus on whether returns on empirically motivated factors represent risks or anomalies. While studies by Fama and French (1993) and Davis, Fama, and French (2000) suggest that the value factor serves as a proxy for distress risks, other scholars argue that it represents persistent mispricing, offering profit opportunities for investors (Lakonishok, Shleifer, and Vishny, 1994; Daniel and Titman, 1997). Daniel, Titman, and Wei (2001) find that outside the U.S., returns on value portfolios (measured by book-to-market ratios) cannot be explained by the risk of the value factor. Furthermore, Asness, Moskowitz, and Pedersen (2013) document that value and momentum strategies consistently generate superior returns across international markets.

Academic researchers generally agree that returns are predictable; however, the line between risk and mispricing is "so blurred that it describes academic politics better than anything substantive" (Cochrane, 2011, p. 202). From an investor's perspective, this academic debate is unlikely to be a primary concern. Rather, given the long history of value investing in the asset management industry (Graham, Dodd, and Cottle, 1934) and the widespread popularity of factor investing, it is plausible that investors treat factor tilts as strategies to seek outperformance.[3] If this is indeed the case, investors

[3]Consistent with this idea, State Street Global Advisors (SPDR), for example, explains smart-beta strategies as follows: "Smart beta strategies aim to give investors the opportunity to potentially achieve higher returns than the traditional market-capitalization indices,... Smart beta strategies seek to capture specific performance factors to deliver an excess return over an index–similar to an active investment strategy." According to Morningstar, such strategies aiming to provide exposure to

are likely to use market betas to discount fund performance (i.e., they reduce flows into funds with high betas), while increasing flows into funds with higher exposures to other factors. Our study aims to investigate this hypothesis and shed light on how investors perceive and respond to funds' factor exposures in their investment decisions.

Our database of global asset managers has several novel features that make it a prime environment to test the above hypothesis. First, asset pricing factors are empirically developed to explain U.S. stock returns. As Berk and Van Binsbergen (2017) argue, these factors can be independently tested on fund flows, which they were not originally intended to explain. Most existing tests, however, focus exclusively on fund flows in the U.S., remaining close to where the asset pricing factors are developed. In this spirit, global fund flows offer a true out-of-sample, independent examination of the relevance of asset pricing factors.

Second, while prior literature predominantly focuses on mutual funds' retail investors, we instead examine global funds' institutional investors (e.g., pension funds and insurance companies), who can invest directly in global asset managers located outside of their home country.[4] Since these institutional investors are larger in size and sufficiently sophisticated (Evans and Fahlenbrach, 2012; Evans and Sun, 2021; Jones, Martinez, and Montag, 2023), they are more likely to possess an understanding of risk, especially the concept of market beta, which is taught in almost all finance courses globally. As such, their capital allocation provides valuable new insights into the aforementioned debate. On the other hand, institutional investors could still be subject to the pressure of chasing past performance and agency problems (Lakonishok, Shleifer, Vishny, and Perry, 1992; Goyal and Wahal, 2008; Jones and Martinez, 2017). Most institutional investors hire asset consultants; however, these consultants may not add value and their recommendations could be based on reasons unrelated to risk-return analyses (Jenkinson, Jones, and Martinez, 2016; Goyal, Wahal, and Yavuz, 2024). Ultimately, it remains an empirical question as to whether global institutional investors account for asset pricing factors in

known factors have grown to \$1.5 trillion as of 2022. This popularity further supports the notion that investors likely perceive exposures to factors as alpha strategies.

[4] Busse, Goyal, and Wahal (2014, p. 561) note that "institutional products are not the same as (and should not be confused with) the institutional class of traditional retail mutual funds." While some small institutional investors and accredited investors may invest in the institutional class of mutual funds, most institutional investors, especially global institutional investors, invest in institutional products.

their capital allocation decisions.

Third, to derive implications regarding the relevant asset pricing model for estimating the global cost of capital, it is crucial to establish a connection between global investors' flows, driven by an asset pricing model, and global equity prices. Such implications, however, have not been examined in the international context, possibly due to the lack of detailed holdings data. Our study is among the first in the literature to employ granular holdings data from global asset managers to investigate the global asset pricing implications of flow-induced trades.

To carry out our tests, we obtain Nasdaq eVestment data on global investment products (henceforth, funds) that adopt a diversified equity strategy, investing across global markets rather than concentrating on a specific country.[5] Following previous research (e.g., Barber, Huang, and Odean, 2016, and others), our empirical analysis begins with a horse race, where we compare the relationship between global fund flows and alphas estimated using prominent global asset pricing models: the CAPM and the Fama and French's (1993) three-factor model and the four-factor model that adds the momentum factor (Carhart, 1997).[6] Our headline results are that global fund flows are more sensitive to the CAPM alpha compared to both past performance and alphas estimated using multi-factor models. Our findings remain robust when we use alternative comparison approaches that account for the nonlinearity between flows and performance. Placebo analysis using global passive funds yields insignificant relations between flows and alphas, suggesting that our findings are not spurious (Ben-David, Li, Rossi, and Song, 2022b).

We next examine whether global investors consider market betas as a risk but treat other factors as alphas. To this end, we employ the return decomposition approach of Barber, Huang, and Odean (2016). This approach involves regressing global fund flows on components of a fund's returns: the fund's alpha and returns derived from

[5] "Funds" in our sample refer to institutional products that are offered to global investors. These products typically use the MSCI All Country World index as their benchmark. Following Gerakos, Linnainmaa, and Morse (2021), we refer to these products as "funds" for ease of exposition and to maintain consistency with prior studies in the flow-alpha literature.

[6] The prevailing literature generally does not find evidence that investors take other factors into account beyond these models. Consequently, we align our analysis with the literature by considering the four factors of Fama and French (1993) and Carhart (1997). Size, value, and momentum also have the highest visibility in the investment industry.

four factors, namely, market beta, size, value, and momentum. A lower coefficient on a factor-related return component indicates that global investors perceive the factor as risk and hence, use it to discount fund performance. By contrast, a higher coefficient indicates that investors see the factor as an alpha strategy, leading to increased flows into funds that exhibit strong performance in that specific factor.

We find that global fund flows are negatively related to the component of beta-related returns, although the effect is not statistically significant. Conversely, flows are positively associated with other factor-related components and are particularly strong for the value factor. These findings indicate that global investors discount funds based on market beta, but they consider factors, particularly value, as strategies for generating alpha.[7]

The above findings pertaining to the value factor combine funds of all investment styles, potentially masking the capital allocation decision of value investors based on the value factor. We therefore conduct a subsample analysis based on fund managers' self-described styles, namely, value, growth, and core styles, where the core style includes strategies that select growth stocks at a reasonable price (i.e., stocks that trade at a price lower than its fundamental value). We draw two main conclusions from this analysis. First, we compare the response of flows to individual return components between growth funds and core funds. Since core funds explicitly use a value tilt to identify cheap stocks among growth stocks, value is explicitly a source of alpha for these funds. If investors of core funds perceive such value constraints as introducing value exposure to the strategy and hence loading on value risk, then the response of flows to the value-related return component of these core funds should be small compared to that of growth funds. On the other hand, if investors of these funds perceive the value tilt as a source of alpha, then we expect the effect of value-related returns on flows to be larger for core funds. Our results are consistent with the latter. We find that the effect of the value-related component for core funds is approximately 50% larger than that for growth funds.

Another notable finding of this subsample analysis is from value funds. Since investors of value funds desire to benefit from the value effect, their flows to these funds

[7]We find that before 2010, investors considered size to be an alpha opportunity. However, between 2011 and 2023, this effect becomes insignificant. This result aligns with the idea that investors gradually gain knowledge about the disappearing size effect (Schwert, 2003).

enable us to more cleanly examine their perception of the value factor. Specifically, if these investors perceive value as a risk factor, their flows to value funds should be driven solely by alpha and not by the value-related return component of these funds. However, we continue to find an economically significant effect of value-related returns on fund flows. Again, these results suggest that even investors of pure value funds perceive the value exposure as a source of alpha, rather than risk.

Our next analysis takes advantage of the breakdown of flows originated by various types of global investors and examines whether these investors use different benchmarks for evaluating fund performance. First, we compare flows from investors with a large mandate to those from investors with a small mandate. Our findings show that investors with a large mandate are less responsive to factor-related returns, although they still allocate more flows to funds with higher value-related returns. Second, we analyze flows from high-net-worth individuals, insurance companies, and pension funds. We find that flows from high-net-worth individuals are the most responsive to factor returns, including market beta, while flows from pension funds are the least responsive. Nevertheless, even pension funds, which are presumably more sophisticated, do not seem to discount factor-related returns as much as they discount beta-related returns. Consistent with our hypothesis, these results suggest that larger institutional investors are sophisticated enough to use the CAPM beta as their benchmark, but they treat factor-based strategies as alpha opportunities.

If global investors use an asset pricing model in their capital allocation decision, their correlated demand induced by the same asset pricing model can cause systematic price fluctuations in the stock market. To examine this prediction, we use detailed holdings data of global asset managers in our sample. We compute an aggregate measure of flow-induced trading across all funds, where flows are predicted by the CAPM, the three-factor model, or the four-factor model. Examining the return predictability of this measure, we find that stocks that were heavily bought by global funds with CAPM-induced inflows subsequently outperform stocks that were heavily sold by global funds with CAPM-induced outflows. This outperformance reverses in the long run, although the reversal effect is weaker, possibly due to the short sample period 2003-2023. We, however, do not find significant return differentials when we use the three-factor model or the four-factor model to predict flows.

The above findings are consistent with the flow-induced price pressure effect (Coval and Stafford, 2007; Lou, 2012; Ben-David, Li, Rossi, and Song, 2022b). They are also in line with the prediction of demand-based asset pricing theory in which institutional investor demand can influence prices (Vayanos and Woolley, 2013; Koijen and Yogo, 2019; Gabaix and Koijen, 2021). Vayanos and Woolley (2013), for example, show that momentum effects can arise when fund outflows are gradual and push prices away from fundamentals, causing a continuation in stock returns in the short run and reversals in the long run as prices correct toward the fair value. Gabaix and Koijen (2021) show that capital flows in and out of the stock market, even small, can have amplifying impacts on prices.[8]

Our study contributes to the contemporary literature that examines the relevance of asset pricing factors using fund flows as a laboratory. As mentioned above, our study is among the first to provide new insights from the perspectives of global institutional investors. Drawing parallels to the evidence from U.S. mutual funds reviewed above, our findings that global investors perceive market betas as risk are surprising, especially in light of the evidence of Barber, Huang, and Odean (2016) and Ben-David, Li, Rossi, and Song (2022b). Barber, Huang, and Odean (2016) find that, while mutual fund investors respond to the CAPM alpha, they do not appear to perceive market beta as risk. More recently, Ben-David, Li, Rossi, and Song (2022b) show empirically that flows from U.S. mutual fund investors blindly follow Morningstar ratings.[9] Our findings suggest that the CAPM and market risk remain important after all, at least in the global asset management sector.

Our paper fits into a nascent strand of literature that explores the global asset management sector. Existing studies have primarily examined the performance of global funds and its persistence (Dyck, Lins, and Pomorski, 2013; Busse, Goyal, and Wahal, 2014; Goyal, Wahal, and Yavuz, 2024; Gerakos, Linnainmaa, and Morse, 2021). Our focus is different. We aim to investigate the relationships between flow and risk fac-

[8] Teo and Woo (2004) and Froot and Teo (2008) find that style investing by fund managers can predict future style returns.

[9] Huang, Li, and Weng (2020) show that Morningstar rating reflects a fund's reputation and thus, chasing those ratings can be a rational behavior.

tors/alpha, as well as whether these relationships differ across investor types, namely, pension funds, insurance companies, and high-net-worth individuals. Our findings directly contribute to the quest to ascertain which asset pricing factors hold significance in global markets.

Our study also aligns with the burgeoning research on institutional (separate account) investors, exploring various dimensions of their operations and impacts. Prior research has examined their skills in selecting asset managers (Brown, Gredil, and Kantak, 2023; Jones, Martinez, and Montag, 2023; Goyal, Wahal, and Yavuz, 2024), the dynamics between these investors, asset consultants, and associated agency conflicts (Jones and Martinez, 2017; Chaudhuri, Ivković, and Trzcinka, 2018; Cookson, Jenkinson, Jones, and Martinez, 2022; Andonov, Bonetti, and Stefanescu, 2023), diseconomies of scale in this sector (Evans, Rohleder, Tentesch, and Wilkens, 2023; Huang, Lu, Song, and Xiang, 2023), and the performance of their investments (Ferson and Khang, 2002; Busse, Goyal, and Wahal, 2010; Elton, Gruber, and Blake, 2014). Other studies compare and contrast the preferences of U.S. institutional investors and mutual fund investors as reflected in their flows (Del Guercio and Tkac, 2002; Evans and Fahlenbrach, 2012; Jiang and Yuksel, 2017). However, these studies do not address competing asset pricing models, nor do they extend beyond U.S. domestic funds.

Given our focus on institutional investors, who are presumably more sophisticated, one might contend that our findings are not surprising. However, in light of studies by Evans and Sun (2021) and Fedyk (2023), who examine the asset pricing factors driving flows into U.S. domestic institutional funds, we argue that global institutional investors' preferences are not entirely predictable *ex-ante*. While Evans and Sun (2021) demonstrate that flows to domestic institutional twin funds are sensitive to the three-factor model, Fedyk (2023) finds that even U.S. separate account investors tend to follow Morningstar ratings, exhibiting behavior similar to their retail counterparts. These divergent findings within the U.S. asset management sector reinforce the necessity for new insights from global markets.[10] Consequently, our study offers much-needed out-

[10]According to Evans and Sun (2021, p. 70), Morningstar ratings for institutional products were not available to investors until 2004. Our findings remain robust when we focus on the subsample period before 2004, indicating that the Morningstar rating does not fully account for our results. Moreover, our global findings reveal that high-net-worth individuals are less sophisticated, aligning their investment behavior more closely with U.S. mutual fund investors. To the extent that the U.S.

of-sample evidence for this ongoing debate. More importantly, we are also the first to use global funds' holdings data and examine the pricing impact of global funds' trading activities that are induced by global investors' use of an asset pricing model. This finding enables us to draw broader implications, including the relevance of various asset pricing models for international capital budgeting.

2 Data and variable construction

We obtain our data from three key sources: actively managed, global equity funds obtained from Nasdaq eVestment, monthly returns on individual stocks listed on international exchanges from Compustat Global, and global index returns from Factset. In what follows, we outline the construction of our sample and describe the characteristics of global funds in our sample.

2.1 Global institutional products

Data on global institutional products come from Nasdaq eVestment, a prominent data provider to plan sponsors, investment consultants, and asset managers. Existing studies that use Nasdaq eVestment data include Jenkinson, Jones, and Martinez (2016), Jones and Martinez (2017), Jones, Martinez, and Montag (2023), Huang, Lu, Song, and Xiang (2023), Goyal, Wahal, and Yavuz (2024).[11] An institutional product refers to a strategy managed by a fund manager, and institutional investors invest in the product through separate accounts, which give them direct ownership of the underlying stocks. For ease of exposition, we use the terms "products" and "funds," interchangeably. Once a product enters the database, it remains there even after the product is closed. As such, the database is free of survivorship bias (Jones, Martinez, and Montag, 2023; Goyal, Wahal,

have an outsized proportion of high-net-worth individuals compared to other countries (Knight Frank, 2021), Fedyk's (2023) results are consistent with our findings that high-net-worth individuals tend to use less complex benchmarks to evaluate funds than institutional investors.

[11] Another source of fund data used in the literature is Morningstar. While Morningstar is more popular in academic research, Nasdaq eVestment is a more specialized vendor in the institutional space (Jones, Martinez, and Montag, 2023; Huang, Lu, Song, and Xiang, 2023). Given Nasdaq eVestment's widespread use among asset owners (we elaborate on this point below), data from this database are highly relevant to our research question.

and Yavuz, 2024).

Nasdaq eVestment obtains their data directly from asset managers.[12] While the data are self-reported, several mechanisms exist to ensure the accuracy of the data. First, asset managers have strong incentives to report accurately and be included in the database, because it enhances their funds' visibility, enabling them to tap into Nasdaq eVestment's significant client base. For example, the Government Pension Investment Fund (GPIF) of Japan, one of the world's largest pension funds with approximately $1.5 trillion in total AUM, discloses that they access asset managers' investing strategies via Nasdaq eVestment platform.[13] Appendix Table A.1 presents a partial list of Nasdaq eVestment clients' names, spanning from major public pension funds such as Calpers (the largest public pension in the U.S. with over $469 billion in AUM) and the Australian Super fund (the largest pension fund in Australia with more than $200 billion in AUM) to corporate pensions (AT&T, Google, Shell, etc.). According to Nasdaq eVestment, 80% of the world's top 50 asset consultants use their data to assess asset managers globally. Several large asset managers such as BlackRock and AQR Capital Management also disclose their use of Nasdaq eVestment data in their in-house research (BlackRock, 2023; AQR, 2017). Given that institutional investors rely on this database to oversee trillions of dollars in assets, it is likely that they trust the database to be of investment quality. Second, all funds in our sample comply with GIPS reporting requirements, further enhancing the accuracy of reported data (Goyal, Wahal, and Yavuz, 2024). Third, Nasdaq eVestment data undergo cross-checking and verification by the clients themselves. Asset consultants and institutional investors leverage Nasdaq eVestment data for routine comparisons between their current fund managers and prospective ones. Through this process, they could evaluate and verify the accuracy of the data, especially for products in which they have invested.[14]

[12] In October 2023, Nasdaq eVestment database also incorporates historical data collected by Mercer, one of the largest investment consultants with $16.2 trillion in global assets under advisement.

[13] In a public document issued to global asset managers, GPIF advises that "GPIF can access the applicant's strategy if it is registered in the eVestment database, and thus applicants will not be required to update performance data if their strategy is registered therein."

[14] During our discussion with a pension fund on how they use Nasdaq eVestment data, we learned that their quest for a potential fund manager typically commences with research on the Nasdaq eVestment platform. Simultaneously, they solicit recommendations from an asset consultant. Based on the client's investment objectives, the consultant typically suggests a list of potential products and their associated Nasdaq eVestment product identifiers. As the final investment decisions rest with the pension fund's managers, these unique identifiers enable the pension fund's managers to conduct

Our study focuses on the global asset management sector within the Nasdaq eVestment database over the 2003–2023 period. These global funds (products) have a worldwide investment mandate, which invests globally without a specific focus on any particular market. Due to this global mandate, according to Nasdaq eVestment, the typical benchmark for these funds is the MSCI All Country World Index (ACWI). Nasdaq eVestment provides us with indicators for each investment strategy employed by a fund, which we use to identify actively managed equity funds, removing index/passive funds from our analysis. In addition, we mitigate the impact of small funds on our analysis by eliminating funds with assets under management of less than $10 million or that hold fewer than 10 stocks (Elton, Gruber, and Blake, 2001). We also remove the first 18 months of data for each fund to reduce the effect of incubator bias (Evans, 2010).

To be included in our sample, we require a fund to have valid data on net returns, which account for management fees and expenses (measured in USD at the monthly frequency). Since a product may have multiple vehicles created for various investors (who invest in the same underlying portfolio of the product), asset managers calculate net-of-fee returns using the average fee for the default/representative vehicle of each product, which we use as our main measure of fund performance. Total net assets reported in USD are measured for the whole product, aggregating across vehicles.

Given the focus of our study on global capital flows, our sample does not contain global funds that serve domestic clients only. For example, we do not include global funds based in the U.K., who serve U.K. clients only and hence, do not report performance in USD, even though these U.K. funds have a global mandate. Following the vast majority of the literature, we compute net flows into fund p in month t, $Flow_{pt}$, as the percentage growth of new assets: $Flow_{pt} = \frac{TNA_{pt}}{TNA_{p,t-1}} - (1 + R_{pt})$, where TNA_{pt} is the total net assets under management of fund p at the end of month t, and R_{pt} is the fund return in month t.

We also obtain from Nasdaq eVestment data on fund AUM disaggregated by regions (i.e., the fraction of a fund total AUM that comes from investors domiciled in a particular region), by investors' mandate size, and by investor types (e.g., pension plans, insurance, high-net-worth individuals, etc.). Our tests of pricing implications of investor preferences

additional research independently on the Nasdaq eVestment platform.

require data on the portfolio holdings of individual products, which are also sourced from Nasdaq eVestment.

Last, we source data on MSCI indices from Factset. Specifically, we use the MSCI All Country World index (ACW) as a proxy for global market returns. The global size factor is the return differential between the MSCI ACW Small Cap index and the MSCI ACW Large Cap index. The global value factor is the return differential between the MSCI ACW Value index and the MSCI ACW Growth index, while the global momentum factor is the return on MSCI ACW Momentum index (in excess of the risk-free-rate). Following the vast majority of literature on international asset pricing (Busse, Goyal, and Wahal, 2014; Fama and French, 2017; Jensen, Kelly, and Pedersen, 2023), we use the U.S. one-month Treasury bill rate as a proxy for the risk-free rate.

2.2 Characteristics of the global asset management sector

After applying the aforementioned filters to fund characteristics, the resulting sample comprises 208,956 fund-month observations spanning from 2003 through 2023. Figure 1 depicts the growth of the number of global funds (products) and total AUM of these funds in our sample, while Table 1 reports yearly descriptive statistics. On average, our dataset includes over 2,300 global funds annually. The number of global funds shows a steady increase over the years.

In line with the above trend, we also see a rise in total AUM over time. Starting at \$594 billion in 2003, the total AUM peaks at \$6 trillion in 2021, before dropping to about \$4.9 trillion in both 2022 and 2023. This decrease in total AUM in 2022 aligns with the trends of global equity markets, following the conclusion of the low interest-rate environment post-Covid-19 (Morningstar, 2023). On average, the global public equity sector has \$3.3 trillion in AUM. This average compares favorably to the sample used in Gerakos, Linnainmaa, and Morse (2021) in which the average values of total AUM of global and U.S. public equity funds are \$2.7 trillion and \$2.8 trillion, respectively, despite the fact that their definition of "global funds" is more generous than ours.[15]

[15] Gerakos, Linnainmaa, and Morse (2021) incorporate overseas domestic funds within the global asset class. For instance, a domestic Australian equity fund that exclusively invests in Australian equities is also included in their sample, while our sample does not contain these funds. Moreover, given that the focus of our study is on global capital allocation, we do not include global funds that do not tend

Table 1 also reports that the average global fund invests in 58 stocks in a given year, indicating that these funds are concentrated. Given the large amount of asset under management, such concentration of holdings suggests that the price impacts of these funds' correlated trades can be meaningful. Figure 2 illustrates the distribution of funds according to fund managers' investment styles (core, value, and growth) over time. Core style consistently maintains its popularity, with its numbers steadily outpacing the other two styles. By 2023, there are over 1,000 core funds. Growth style follows as the second most prevalent, with nearly 800 funds in 2023, having shared a comparable level of popularity with the value style until 2019.

Table 2 displays the geographic distribution of global funds, which are domiciled in 27 countries. The top five countries with the largest number of global funds are the U.S. (2,825 funds), the U.K. (554 funds), Canada (157 funds), Switzerland (85 funds), and Germany (63 funds). Countries with the fewest representatives in our sample include the United Arab Emirates, Saudi Arabia, and South Korea, each with three funds. Asset managers in the U.S. manage an outsized portion of global investment capital, overseeing \$3.6 trillion, representing 72% of the total delegated capital in 2023.

Table 3 presents year-by-year statistics on global capital flows. On average, the aggregate net flow (i.e., inflow minus outflow) across all global funds is \$46.9 billion per year. An average global fund receives \$52.9 million in net flow annually, representing 4.2% of its assets under management. During our sample period, the global asset management sector experienced two major episodes of net outflows: the Global Financial Crisis in 2008 and the conclusion of the low interest-rate era post-Covid-19 in 2022–consistent with the pattern in global AUM observed in Table 1.

In Table 4 panel A, we present descriptive statistics of other fund characteristics, pooling across all fund-month observations. The average fund age is 119 months (about 9.9 years), while the median age is 88 months (7.3 years). The mean monthly return volatility of sample global funds is 4.7%. While the mean net return (without adjusting for risk factors) is 1.8%, the average four-factor alpha is -0.06% per month, indicating that a typical global fund underperforms once known risk factors are considered (Appendix A provides a detailed description of the methodology to estimate fund alphas

to serve overseas investors.

and betas). The average fund exhibits market beta, size, value, and momentum loadings of 1.0, 0.18, -0.11, and 0.05, respectively. This suggests that the average fund closely mirrors market risk, with some exposure to smaller stocks and growth stocks and almost zero tilt toward momentum stocks.

Table 4 panel B displays the correlation matrix for various performance measures, including CAPM alpha, three-factor alpha, four-factor alpha, and unadjusted returns (net returns in excess of the risk-free rate, proxied by U.S. Treasury bill rates). The correlations among these performance measures are strong, ranging from 0.56 to 0.92. Flow shows the highest correlation with CAPM alpha (0.08) and the lowest with unadjusted returns (0.01).

3 Empirical analysis

In this section, we first conduct a horse race to compare the explanatory power of competing asset pricing models in explaining global fund flows. We then analyze fund returns by separating them into components related to various factors. This test allows us to examine whether global investors regard an asset pricing factor as risk and opportunities for alpha, as well as examining the investor sophistication hypothesis. Last, we investigate the effect of global investors' use of an asset pricing model on international stock prices.

3.1 Global fund flows and competing measures of fund performance

3.1.1 Which performance measures drive cross-sectional flows?

We begin our empirical analysis by estimating the regression of one-month-ahead fund flows on different measures of fund performance. As in Barber, Huang, and Odean (2016), our null hypothesis is that, if global investors are fully rational and sophisticated, they should consider all factors that explain fund performance when making investment decisions. However, as we discussed in the Introduction, the question of which asset pricing models global investors use to allocate flows is ultimately an empirical one. Following the majority of the literature (e.g., Ben-David, Li, Rossi, and Song, 2022b), all regressions include controls for year-month fixed effects, and standard errors are double-clustered at the year-month and fund levels. We do not include control variables because including "bad controls" can potentially bias the coefficient of interest (Angrist and Pischke., 2009; Gormley and Matsa, 2011).[16] Nevertheless, we confirm that our results do not qualitatively change if we include standard control variables such as fund expense ratio, historical average flows over the past 18 months, the natural logarithm of fund age, fund volatility (the standard deviation of fund returns estimated using 18-month rolling windows), the natural logarithm of fund size (AUM), fund-level exposure to the U.S. inflation index (estimated using the same methodology for market betas but replacing the excess market return with the U.S. CPI), fund-level exposure to the world inflation index (world CPI obtained from the World Bank), and fund-level exposure to the world GDP growth (obtained from the World Bank).[17]

Table 5 reports the estimation results. Column (1) presents the regression of net flow into fund p in month $t+1$ ($Flow_{p,t+1}$) on unadjusted return of fund p in month t. The coefficient on unadjusted returns is positive and statistically significant at the 1% level, suggesting that global fund flows are positively associated with fund past performance. However, once we include the CAPM alpha in Column (2), the coefficient on unadjusted returns becomes negative and statistically significant, while the coefficient on the CAPM alpha is 0.95 with an associated t-statistic of 4.9, which is significant at the 1% level. These results suggest that the CAPM alpha is a more dominant driver of global flows than past fund performance. In Column (3), we replace the CAPM alpha with the three-factor alpha and find that the coefficient on the three-factor alpha is 0.34 (t=2.22), comparable to the coefficient on unadjusted returns, which is 0.36 (t=2.55). Similarly, in Column (4), the coefficient on the four-factor alpha (0.35) closely matches the coefficient for unadjusted returns (0.35). Columns (5) and (6) demonstrate

[16] Gormley and Matsa (2011) point out that if the variable of interest impacts a control variable, then including the control variable can bias the interpretation of the main coefficient. For example, suppose that the three-factor alpha matters more than the CAPM alpha. In this case, funds with a high three-factor alpha can attract inflows, which, in turn, affect all other control variables. Including control variables potentially yields a coefficient on the three-factor alpha that is close to zero—-even though the three-factor model is the underlying model causing the changes in all other control variables.

[17] The number of observations drop by a third when we include controls.

that, after controlling for the CAPM alpha, the coefficients on the three-factor alpha and the four-factor alpha become economically negligible and statistically insignificant. These results further underscore that the CAPM alpha remains the dominant model in explaining global fund flows.

Alternative estimation approach: Fama-MacBeth cross-sectional regressions. The cross-sectional regression, while a common approach used in the literature, may potentially place more weight on periods of extreme market movements, which could adversely impact our results (Ben-David, Li, Rossi, and Song, 2022b). In Appendix Table A.1, we employ the Fama-MacBeth regression approach, which applies equal weights to all months during the sample period. We continue to find that the CAPM alpha is the strongest predictor of future global fund flows, and it drives out all other performance measures.

Placebo analysis using passive funds. Ben-David, Li, Rossi, and Song (2022b) argue that any evaluation of asset pricing factors based on the revealed preferences of fund investors should include falsification tests using passive funds. Given that alphas are irrelevant for passive funds, we expect the relationship between flows and various performance measures to be insignificant. In Appendix Table A.2, we replicate the regressions from Table 5 using a sample of global passive funds sourced from Nasdaq eVestment.[18] We find that none of the coefficients on the performance measures are significant, even at the 10% level. These findings suggest that our conclusions in Table 5 are robust and not the result of spurious correlations.

Do global investors chase Morningstar ratings? The U.S. literature indicates that not only do mutual fund investors follow Morningstar performance ratings (Ben-David, Li, Rossi, and Song, 2022b), but separate account investors of U.S. domestic equity funds also appear to consider these ratings in their capital allocation decisions (Fedyk, 2023).[19] A natural question, therefore, is whether the Morningstar ratings of

[18]On average, the sample comprises 199 global passive funds each year, and the average passive fund has an AUM of $4.6 billion.

[19]Gorbatikov (2023) finds that after accounting for the stale information in Morningstar ratings, the sensitivity of flows to these ratings is reduced significantly, and flows induced by Morningstar ratings

global funds also drive our findings. Ben-David, Li, Rossi, and Song (2022b) argue that if investors are influenced by Morningstar ratings, then flows into passive funds should also correlate with alphas and past fund performance, which are closely linked to these ratings. As we discussed above, our placebo analysis using passive funds shows insignificant results, suggesting that Morningstar ratings are unlikely to drive our results.

To further address the concern about the potential influence of Morningstar ratings, we focus on the subsample prior to 2004. Since Morningstar ratings are primarily aimed at individual retail investors,[20] similar ratings for institutional products only became available on Morningstar investment platforms starting from 2004 (Evans and Sun, 2021). According to Morningstar, a rating is not available in the following cases: (1) an institutional fund chooses not to participate in the rating scheme; (2) the fund has fewer than five separate accounts (as institutional products typically have few investors, each investing hundreds of millions of dollars, this constraint can potentially disqualify many funds of interests); (3) the fund is less than three years old; or (4) the fund is not AIMR-compliant. Perhaps due to these constraints, Fedyk (2023) notes that Morningstar ratings are not available for most U.S. domestic equity institutional products. Morningstar uses the same methodology to rank both retail mutual funds and institutional funds.[21]

We re-estimate the regressions of Table 5 using the sample of global funds before 2004 and report the results in Appendix Table A.3.[22] As Morningstar ratings for institutional products were not available during this period, our analysis is unaffected by these ratings. We find that the CAPM alpha remains the strongest predictor of future fund flows among all performance measures. These results again suggest that Morningstar ratings

do not predict subsequent stock returns.

[20]Indeed, Morningstar advertises its products as "Market-Leading Independent Research, Ratings & Tools For *Individual* Investors [our emphasis]." In its methodology document for fund ratings, Morningstar calibrates the risk aversion coefficient based on "the risk tolerances of typical retail investors." The document also explains how they adjust the rating scale such that it is not counter-intuitive to retail investors.

[21]Ben-David, Li, Rossi, and Song (2022a) provides a detailed description of Morningstar's methodology.

[22]For this analysis, we use factor return data from Jensen, Kelly, and Pedersen (2023), which offers a more extensive historical record. We cannot use alphas estimated from MSCI data because MSCI style indices only began in 1998. Given our requirement for 60 months of valid data to estimate regressions, alphas estimated using MSCI data are available from 2003, making them unsuitable for this test. Our final sample for this test starts from 1997 and covers, on average, 656 unique global products each year, with the average product having an AUM of $1.7 billion.

are unlikely to confound our findings.

3.1.2 Pairwise model horse race

We next conduct a pairwise comparison of models using the methodology of Barber, Huang, and Odean (2016). An advantage of this approach is that it addresses the potential non-linearity in the flow-performance sensitivity. It also accounts for the potential collinearity issue that arises from the high correlations between different alpha measures. At the end of each month, we rank and sort global funds into deciles based on each performance measure, where Decile 1 contains funds with lowest performance and Decile 10 comprises funds with highest performance. A fund, for instance, might be placed in Decile 8 according to the CAPM alpha and in Decile 3 based on the three-factor alpha in a specific month. To perform the pairwise horse race, we estimate the following regression:

$$Flow_{p,t+1} = \alpha + \Sigma_i \Sigma_j \beta_{ij} D_{ijpt} + \mu_t + \epsilon_{pt} \quad (1)$$

where $Flow_{p,t+1}$ is the fund flow for fund p in month $t+1$. D_{ijpt} is an indicator that equals one if in month t, fund p belongs to decile i based on model 1 (e.g., the CAPM) and decile j based on model 2 (e.g., the three-factor). We include year-month fixed effects (μ_t) to control for common time trends. Our test involves comparing the coefficients β_{ij} and β_{ji}, where the rankings of funds based on two competing models disagree with each other. For example, we compare the flows between two types of funds: (1) those that belong to decile 9 based on the CAPM alpha and decile 1 based on the three-factor alpha (β_{91}) and (2) those that belong to decile 1 based on the CAPM alpha and decile 9 based on the three-factor alpha (β_{19}). If the CAPM alpha is a stronger determinant of global flows, we expect that $\beta_{91} > \beta_{19}$. Generally, if investors place more weight on model 1 than model 2, then β_{ij} should be greater than β_{ji}, for all $\beta_{ij} \neq \beta_{ji}$. As in Barber, Huang, and Odean (2016), we focus on two evaluation metrics: (1) whether the proportion of positive differences is equal to 50%; and (2) whether the sum of the coefficient differences ($\beta_{ij} - \beta_{ji}$) across all pairwise comparisons is equal to zero.

Table 6 reports the estimation results. In panel A, we compare the CAPM alpha to each of the other competing performance measures. The results show that the CAPM is a superior predictor of global fund flows. Specifically, the sum of the coefficient differences for the CAPM alpha is positive and significant when compared to unadjusted returns, the three-factor alpha, and the four-factor alpha. The proportion of positive coefficient differences (indicating that the CAPM wins in the horse race) is also large, ranging from 80% to 89% of the differences.

In panel B, we compare the coefficient for unadjusted net return with the coefficients for the three-factor alpha and the four-factor alpha, respectively. The results indicate that the proportion of positive coefficient differences is 66.4% (binomial $p = 0.07$) for both comparisons. However, the sums of coefficient differences are statistically insignificant ($p > 0.7$ for both horse races). These findings suggest that past unadjusted returns are not a superior predictor of global fund flows compared to alternative performance measures. Last, panel C compares the coefficient differences between the three-factor alpha and the four-factor alpha. We do not find evidence suggesting that one model is better than the other.

In sum, the results of the pairwise model horse races in Table 6 suggest that CAPM alpha is the superior predictor of global fund flows among the four competing models under consideration.

3.2 Flows to top-ranked global funds

To the extent that investors use a performance measure to rank global funds, we expect the flow-to-performance sensitivity to be more pronounced among the top-performing funds as identified by that performance measure.[23] Figure 3 summarizes the main findings of this analysis (and our study) by depicting the average dollar flows into top and bottom funds as ranked by a performance metric. The figure shows that global flows to top- and bottom-ranked funds are more responsive to the CAPM alpha than to other

[23] Sirri and Tufano (1998b) find that flow-performance relationship is strong for funds whose previous year's returns place them in the top 20^{th} percentile. Chevalier and Ellison (1997) find that fund managers have incentives to take risk, so that they are ranked among the top performers. Huang, Wei, and Yan (2007) theoretically show that, due to the cost of information acquisition, investors are inclined to focus their search on a limited number of funds with superior past performance. Due to the convexity of fund-flow sensitvity, funds have incentives to take risk to attract fund flows (e.g., Brown, Harlow, and Starks, 1996; Koski and Pontiff, 1999; Huang and Zhang, 2016)

measures. For example, using the CAPM alpha as a performance measure, the average dollar flow into top-ranked funds is \$127 million per month, whereas the average flow into bottom-ranked funds is \$10 million per month. While flows to top-ranked funds based on unadjusted returns are closest to the CAPM alpha averaging at \$119 million, flow to bottom-ranked funds based on this measure stands at \$17 million, which exceeds the flow to bottom funds guided by the CAPM alpha. Flows respond more strongly to the four-factor alpha than to the three-factor alpha, yet both models are less effective at explaining global flows compared to unadjusted returns.

To more formally examine the above results, we estimate panel regressions in which we compare the difference in flow-to-performance sensitivity between a pair of indicators for top-ranked performance metrics, following Ben-David, Li, Rossi, and Song (2022b). Specifically, we create a dummy variable that is equal to one if a fund is ranked in the top quintile based on a performance metric each month. We then construct variables to capture pairwise differences in top-ranked fund indicators of different performance metrics. For example, to compare flows to top-ranked funds based on the CAPM alpha and to flows to top-ranked funds based on unadjusted returns, we create two dummy variables: Top_CAPM and Top_UnRet; each variable is set to one if a fund is in the top quintile based on the CAPM alpha or unadjusted returns, respectively, and zero otherwise. We compute the difference between these indicators as $UnRet\_M\_CAPM = Top\_UnRet - Top\_CAPM$. This difference variable, $UnRet\_M\_CAPM$, can take one of three possible values: -1, 0, or 1. We also include the dummy variable, $UnRet\_E\_CAPM$, which equals one if a fund is in the top quintile by both metrics, making $UnRet\_M\_CAPM$ equal to 0. We apply this process to other pairs of top-ranked fund indicators.

Table 7 reports the estimation results. Column (1) compares flows to top-ranked funds based on unadjusted returns and flows to top-ranked funds based on the CAPM alpha. The coefficient on $UnRet\_M\_CAPM$ is negative and statistically significant, suggesting that top-ranked funds based on unadjusted returns receive less inflows than those top-ranked funds based on the CAPM alpha. Similarly, comparisons between the CAPM alpha and either the three-factor alpha or the four-factor alpha (columns (4) and (5)) indicate that top-ranked funds with respect to the CAPM alpha receive more inflows than those ranked in the top by either the 3-factor alpha or the 4-factor alpha. In columns (2), (3), and (6), we find insignificant differences in flows into top-ranked funds based on adjusted returns, the three-factor alpha, and the four-factor alpha.

3.3 Do global investors consider a factor as risk or alpha opportunities?

The findings from the previous sections indicate that the CAPM alpha is a more significant driver of global flows compared to other performance metrics. In this section, we investigate whether global investors view the market, size, value, and momentum factors as risks or as strategies to achieve outperformance. To this end, we follow the approach of Barber, Huang, and Odean (2016) and decompose fund returns into five components, which are attributed to alpha, market, size, value, and momentum. Specifically, alpha is the estimated alpha obtained from the four-factor model, while factor-related returns are computed as the product of a fund's loadings on a factor and the return on that factor. We then estimate the following panel regression:

$$Flow_{p,t+1} = b_0 + b_1\alpha_{pt} + b_2 Market\_Return_{pt} + b_3 Size\_Return_{pt} + b_4 Momentum\_Return_{pt} + b_5 Value\_Return_{pt} + \epsilon_{pt} \quad (2)$$

where α_{pt} is fund p's four-factor alpha; $Market\_Return_{pt}$ is fund p's returns that are related to the market and is computed as the fund's market beta multiplied by market returns. Similarly, $Size\_Return_{pt}$, $Value\_Return_{pt}$, and $Momentum\_Return_{pt}$ are fund p's returns related to size, value, and momentum, respectively.

As Barber et al. (2016) suggest, the primary focus of this return-decomposition analysis is the comparison of the economic magnitude of the coefficients, rather than the statistical significance of a coefficient. Specifically, given investors' strong preference for seeking alpha, a comparison between the coefficient on a return component and the coefficient on alpha informs us about whether investors treat a factor as risk or an alpha opportunity. If investors tend to discount a fund's performance that is derived from increased exposure to a factor, this discount should be reflected in lower flows and hence, a smaller coefficient on factor-related returns compared to the coefficient on alpha. For instance, if global investors view market exposure as a source of risk, we would expect the coefficient b_2 on market-related returns to be smaller than the coefficient b_1 on alpha. Conversely, if investors perceive that funds pursue a style such as growth/value as a means to generate outperformance, we expect the coefficient on the factor-related return to be equal to or even greater than the coefficient on alpha.

In Table 8, we present the estimation results for Equation (2). Column (1) shows the results using the full sample, while Columns (2)-(9) present the result using subsamples split based on time periods, the sign of market-adjusted returns (fund net returns minus the market return), fund AUM, and age. In Column (1), we find that the coefficient b_2 on market-related returns is -0.128 with an associated t-statistic of -0.75, which is statistically insignificant and economically smaller than the coefficient on alpha, b_1, which is equal to 0.69 with a significant t-statistic of 7.4. This result suggests that global investors tend to discount a fund's performance that is attributed to its market risk. The coefficient on size-related return, b_3, and momentum-related return, b_4, are 0.13 (t-statistic=0.45) and 0.18 (t-statistic=0.92), respectively, which are also small (representing 19% and 26% of the coefficient on alpha) and statistically significant. These results suggest that global investors also discount the fund's performance components that are attributed to the size factor and the momentum factor, although flows are still more responsive to these factors than to the market risk. Interestingly, the coefficient on value-related returns, b_5, is 0.75 (t-statistic=3.69), which is larger in magnitude than the coefficient on alpha. This result indicates that global investors tend to perceive value as an alpha strategy and thus, they allocate more capital toward funds with higher value-related returns.

In Columns (2) and (3), we investigate whether global investors' perceptions of asset pricing factors change over time by dividing the sample into two subperiods: pre-2010 and post-2010, roughly the beginning of the recovery of global financial markets after the Global Financial Crisis. We find that the coefficient on market-related returns remains smaller than that on alpha in both sub-periods. However, the coefficient on size-related returns is statistically significant and economically larger than that on alpha during the pre-2010 period. This coefficient becomes negative and insignificant post-2010. These results suggest that while global investors treated the size factor as alpha before 2010, they have discounted funds with higher exposure to the size factor in recent decades. This result is consistent with the evidence that the size anomaly, by itself, has disappeared in international markets (Asness, Frazzini, Israel, Moskowitz, and Pedersen, 2018). The coefficient on value-related returns exhibits a different trend. While this coefficient remains economically similar across both subperiods, it is smaller than the coefficient on alpha before 2010 and is statistically insignificant. In contrast, this coefficient is economically larger than the coefficient on alpha after 2010. These results indicate that global investors have increasingly allocated more flows to funds with higher value-related returns, especially in recent decades. Last, the coefficient on momentum-related returns during the pre-2010 period is -0.03, which is lower than this coefficient of 0.39 (representing 71% of the coefficient on alpha) during the post-2010 period, albeit remaining insignificant. This finding suggests that global investors are progressively treating momentum as an alpha strategy.[24]

To examine whether our results in Column (1) are robust to the nonlinearity of the flow-performance relationship, in Columns (4) and (5), we split the main sample into two groups based on whether the fund has positive market-adjusted net returns. We find that the relative comparisons between the coefficients on factor-related returns and the coefficient on alpha remain qualitatively similar across both groups. In Columns (6) and (7), we divide the sample by the median AUM, finding that regardless of fund size, global flows respond strongly to value-related returns but not to returns linked to market, size, and momentum factors. Finally, in Columns (8) and (9), we separate the sample by the median fund age and observe consistent results across both subsamples.

Where are the global investors? Geographic breakdown of global investors and their responses to components of fund returns In the next analysis, we provide further insights into the preferences of investors from various regions. We employ Nasdaq eVestment data on the breakdown of a fund's AUM by investors' countries/regions, namely, Australia, Asia excluding Japan, Europe, Japan, North America, the United Kingdom, and the rest of the world (RoW). We then calculate the flows from each region into a fund and re-estimate Regression (2), substituting the dependent

[24]In Appendix Table A.4, we confirm that our results remain robust when using the Fama-MacBeth regression approach.

variable with regional flows.

Table 9 reports the estimation results. First, the coefficient on alpha is positive and statistically significant for all regional flows, indicating that institutional investors everywhere are responsive to fund alphas. Second, with the exception of Asia, the response of flows to the market, size, and momentum components of fund performance is significantly weaker than that to alpha, especially for Europe. European investors tend to apply a larger discount on fund performance that is traced to market risk. Asian investors, however, show a strong response to momentum-related returns, with the coefficient on this component being economically larger than that on alpha. Third, we find that Asian investors are not responsive to fund returns traced to the value factor, as the coefficient on this component is close to zero and statistically insignificant. In contrast, investors from Japan, Australia, Europe, and North America respond more strongly to value-related returns than to fund alpha. While the coefficients on value-related returns for flows from the RoW and the U.K. are statistically insignificant, their magnitudes are large, representing 74% and 93% of the coefficient on alpha.

Do global investors' responses to components of fund returns depend on fund styles? To examine whether the responsiveness of global flows to factor-related returns depends on fund styles, our next test partitions the sample of global funds into three groups based on their investing styles: value, growth, and core. Table 10 reports the estimation results. First, we observe consistent results across all fund styles, indicating that global flows are responsive to fund alpha but not to returns attributed to market, size, or momentum factors. Notably, for growth funds, the coefficient on market-related returns is significantly negative, suggesting that investors in growth funds tend to withdraw their capital when the market risk of these funds is higher.

Second, the coefficient on value-related returns is most significant and largest for core funds. Since core funds typically use value criteria as an alpha strategy to select reasonably priced stocks, this result suggests that investors reward these funds with more inflows for increasing their value tilt, rather than discounting it. We also find a significant coefficient on value-related returns for growth funds, equivalent to 97% of the coefficient on alpha, indicating that growth investors also increase flows to growth funds with a value tilt.

A perhaps more surprising result is for value funds, where we find a positive and significant coefficient on value-related returns, equivalent to 67% of the coefficient on alpha. This suggests that even investors in value funds do not discount the performance traced to their exposures to the value factor.

Collectively, the results from Tables 8, 9, and 10 support our hypothesis that global investors fully consider market risk when evaluating fund performance, and consequently do not allocate capital based on fund returns attributed to market risk. Global investors appear to view the value factor as a strategy for generating outperformance rather than as a risk factor. These findings challenge the investor sophistication hypothesis, which suggests that sophisticated investors should discount fund returns related to all factors, regardless of whether a factor is priced. One possible explanation is that even these global investors operate under mandate benchmarks based on market betas, rather than exposures to other factors, naturally causing them to select asset managers based on market betas. While the information on mandate benchmarks of global fund investors is not available, a report by Ang, Goetzmann, and Schaefer (2009) for the Norwegian Ministry of Finance suggests that this could be the case.

3.4 Estimation error in factor loadings

In the previous section, we empirically demonstrate that global investors apply the largest discount to fund performance attributable to beta risk, while they respond positively to fund returns associated with the value factor. A potential concern is that these factor loadings might be noisy, and investors could be discounting this noise in their estimates. Specifically, to the extent that market beta is less noisy compared to other factor loadings, global investors might rationally adjust market beta toward its global mean of one when making capital allocation decisions, while they shrink the loadings on other factors toward the expected mean of zero. Consequently, the coefficient estimate for market-related returns would appear smaller than those for other factor-related returns, even though investors might actually respond equally to all factor-related returns.

The above alternative explanation predicts that the estimation error of market beta will be smaller than that of other factor loadings. To test this prediction, we follow Barber, Huang, and Odean (2016) and calculate the "precision ratio" of out-of-sample factor loadings to in-sample loadings. A higher precision ratio indicates lower estimation errors, as the out-of-sample estimate is closer to the in-sample estimate. To compute the in-sample loading, at the end of each month, we rank and sort funds into quintiles based on a factor loading and compute the average loading for each quintile. We then compute the average loading over time and the associated standard error for each quintile. To estimate out-of-sample loadings, funds are sorted into quintiles based on a factor loading at the end of month t. For each quintile, we then calculate the average return across funds in month $t + 1$. We then estimate the out-of-sample loadings by estimating the time-series regression of the average return on each quintile (in excess of the risk-free rate) on returns on each factor.

We present the estimation results in Table 11. Panel A shows that the in-sample market beta ranges from 0.731 for the bottom quintile to 1.226 for the top quintile, resulting in a spread of 0.495. For the out-of-sample betas, values increase monotonically from the bottom to the top quintile, indicating that the rank ordering of market betas is preserved out-of-sample. The spread between out-of-sample market betas in the bottom quintile and top quintile decreases to 0.218, yielding a precision ratio of 44% (i.e., 0.218/0.495). In Panels B, C, and D, we find that the precision ratios for size, value, and momentum coefficients are 52%, 45%, and 43%, respectively, which are higher than that for the market beta. These results suggest that these factor loadings are estimated with lower noise than the market beta.

3.5 The heterogeneity of investor types

While global investors in our sample are accredited investors, who have the ability to move capital globally, they are a heterogeneous group, ranging from pension funds to high-net-worth individuals. Each investor type is likely to use a different approach to selecting funds. For example, Dyck, Lins, and Pomorski (2013) and Goyal, Wahal, and Yavuz (2024) document that pension funds tend to be more sophisticated, as they employ an investment committee and follow a standardized process for searching and selecting funds. Such a process is likely to be more rigorous than that implemented by high-net-worth individuals. Moreover, investors with a large mandate size also tend to use a more sophisticated benchmark compared to those with a small mandate size (Gârleanu and Pedersen, 2018). We therefore expect that pension funds are more likely to treat market beta as risk. Yet, as we discuss in the Introduction, these investors may treat prominent factors such as value as an anomaly and a strategy to generate outperformance.

To examine the heterogeneity of investor types, we obtain data on investor mandate size and the breakdown of a fund's AUM by pension funds, insurance, or high-net-worth individuals from Nasdaq eVestment. We re-estimated Regression (2), substituting the dependent variable with alternate flow measures for each investor type and report the results in Table 12. In Columns (1) and (2), we partition the sample into two groups based on investor mandate size, where large investors are those with a \$500 million mandate or above and smaller investors have a mandate below \$500 million. We find that both investor types discount funds' market-related returns. Interestingly, large investors apply a larger discount on fund returns that are traced to the fund's exposure to the size factor. In fact, for large investors, the coefficient on the size-related return is negative and statistically significant at the 1% level, suggesting these investors significantly penalize funds for having a high exposure to the size factor. Both large and small investors respond positively to the value-related return component. Large investors' flows tend to more responsive to funds' momentum-related returns compared to small investors, although the difference is not significant.

In Columns (4)-(6), we present the estimation results for flows from high-net-worth individuals, insurance companies, and pension funds. Several results are notable. First, high-net-worth individuals' flows are more responsive to funds' market-related returns, as evidenced by the coefficient on this component being larger in magnitude than the coefficient on alpha. In contrast, the coefficient on market-related returns is negative, albeit insignificant, for both insurance companies and pension funds, suggesting that these institutions treat market beta as a risk factor. Second, for high-net-worth individuals, the coefficient on funds' value-related returns is positive and larger than the coefficient on alpha, whereas this coefficient represents 78% and 59% of the coefficient on alpha for insurance companies and pension funds, respectively. Third, high-net-worth individuals respond more positively to funds' momentum-related returns, whereas pension funds and insurance firms tend to discount this component of fund performance. Consistent with our conjecture, the results show that high-net-worth individuals are the least sophisticated among the three investor types, while pension funds are the most sophisticated.

The results in Table 12 indicate that larger investors, such as pension funds, view market betas as a risk, while high-net-worth individuals generally respond positively to higher market betas. However, all investor types appear to regard the value factor as an alpha strategy. These findings suggest that while global investors are sophisticated enough to understand beta risk, they do not rely on more complex benchmarks in their capital allocation decisions.

3.6 Implications for stock returns: Flow-induced portfolios

The previous section demonstrates that global investors tend to use the CAPM in their capital allocation decisions. In this section, we explore whether the demand for funds with high CAPM alpha can influence global stock returns.[25] According to the demand-based asset pricing theory, correlated investor demand can lead to systematic price changes (Koijen and Yogo, 2019). Additionally, Gabaix and Koijen (2021) show that such correlated demand can result in amplification effects, whereby a 1% increase in investor flows into the equity market can boost the aggregate value of the equity market by up to 5%. Vayanos and Woolley (2013) show theoretically that common flows can cause correlated trades among fund managers, which ultimately lead to momentum effects in the short run and reversals in the long run. Ben-David, Li, Rossi, and Song (2022a) analyze holdings data of U.S. mutual fund and find that Morningstar rating-driven demand by household investors creates price pressure at the style level, which eventually reverses.

To examine the effect of global fund flows on prices, we obtain data on global funds' holdings from Nasdaq eVestment, which are available at the quarterly frequency. For

[25] Goetzmann, Massa, and Rouwenhorst (2000), Ferson and Kim. (2012), and Dou, Kogan, and Wu (2024) show that fund flows exhibit a strong common structure and vary at a lower frequency than business cycles. Huang, Song, and Xiang (2024) find that noise trading induced by flows of retail investors exacerbates anomalies.

each global fund (product), we observe stock identifiers (ISIN, SEDOL, or CUSIP), number of shares, and the value of the stock holdings at the end of each quarter. For each stock in a fund's global portfolio, we collect data on returns, prices, and market capitalization from Jensen, Kelly, and Pedersen (2023), who, in turn, obtain the data from Compustat Global, CRSP, and Compustat North America.[26] We follow Lou (2012) and construct a measure for flow-induced trading (FIT) for each stock each month as:

$$FIT_{j,t} = \frac{\sum_i shares_{i,j,t} \times \widehat{Flows}_{i,t}}{\sum_i shares_{i,j,t-1}} \tag{3}$$

where $shares_{i,j,t}$ is the number of shares of stock j held by fund i at the end of month t. $\widehat{Flows}_{i,t}$ is the fitted value obtained from the return decomposition regression shown in Table 8 column (1). We estimate $\widehat{Flows}_{i,t}$ using three distinct models: the CAPM, the three-factor model, and the four-factor model. For the CAPM, we derive the CAPM-flow-induced trading for individual stocks, denoted as $FIT\_CAPM_{j,t}$, based on flows predicted by the CAPM's alpha and market risk-related returns. In a similar vein, the three-factor-flow-induced trading, denoted as $FIT\_FF3_{j,t}$, is estimated using fund flows predicted by the three-factor model, incorporating alpha, market risk, size, and value-related returns. Lastly, the four-factor-flow-induced trading, denoted as $FIT\_FF4_{j,t}$, uses fund flows forecasted by the four-factor model, comprising alpha, market risk, size, value, and momentum-related returns. At the end of each month t, we rank and sort stocks into quintiles based on each of the above flow-induced trading estimated in month $t-1$. We then compute value-weighted returns on each of the quintiles over the holding periods ranging from $t+1$ to $t+72$ months. To avoid bid-ask bounce and other market microstructure effects, we skip a month between the formation month $t-1$ and the prediction month $t+1$ (Jegadeesh, 1990). To further mitigate the influence of microcap stocks, we remove stocks that are priced below \$5 in month $t-1$ (Jegadeesh and Titman, 2002).[27]

In Table 13, we report the return differential (spread) between the top portfolio (comprising the most heavily purchased stocks) and the bottom portfolios (consisting of the most heavily sold stocks), constructed using alternative flow-induced trading

[26]These data are maintained by WRDS.

[27]Our results also remain robust when we remove stocks with market capitalization smaller than the 20^{th} percentile, computed for each exchange in month $t-1$.

measures. Panel A presents the alphas of these portfolios estimated using the four-factor model. Examining the one-month-ahead holding period, we find that the spread portfolio constructed based on $FIT\_CAPM_{j,t}$ yields an alpha of 0.94% with an associated t-statistic of 2.3, which is statistically significant at the 5% level. This alpha is greater than the alphas on the spread portfolios constructed using $FIT\_FF3_{j,t}$ and $FIT\_FF4_{j,t}$, which are 0.24% (t=1.52) and 0.27% ($t = 1.75$), respectively. These results indicate that stocks experiencing common inflows as predicted by the CAPM generate a higher four-factor alpha compared to those subject to outflows under the same model. In contrast, flows predicted by the three-factor and four-factor models show no significant impact on prices, underscoring the CAPM as the most pertinent model for influencing stock prices among the models considered.

Extending the holding period reveals a significant decline in spreads within flow-induced portfolios over 12 months, eventually turning negative and weakly significant over 72 months. The lack of statistical significance is possibly due to the relatively short sample, which is not sufficient to detect reversals. Nevertheless, the weak long-run reversals are consistent with the price pressure effect posited by demand-based asset pricing theory.

In panel B, we conduct spanning tests whereby we use returns on the $FIT\_FF3_{j,t}$ portfolio and the $FIT\_FF4_{j,t}$ portfolio to explain returns on the $FIT\_CAPM_{j,t}$ portfolio. The results reveal that, even after accounting for the $FIT\_FF3_{j,t}$ and $FIT\_FF4_{j,t}$ portfolios, the alpha of the $FIT\_CAPM_{j,t}$ portfolio stands at 0.64% ($t = 2.2$), which is significant at the 5% level. Conversely, after adjusting for returns on the $FIT\_CAPM_{j,t}$ portfolio, the alphas on $FIT\_FF3_{j,t}$ and $FIT\_FF4_{j,t}$ portfolios are 0.21% ($t = 1.6$) and 0.25% ($t = 1.8$), respectively, both of which are smaller than the alpha of the $FIT\_CAPM_{j,t}$ portfolio. These results reinforce our conclusion that the CAPM remains the most influential model in affecting stock prices.

4 Conclusion

The global asset management industry is primarily dominated by accredited investors, distinguished as some of the most sophisticated investors with the capability to allocate capital on a global scale. This industry, therefore, offers a prime out-of-sample laboratory to examine the relevance of asset pricing factors in the global markets. Examining this question has implications for both asset pricing and corporate finance. In the realm of asset pricing, the growing number of asset pricing factors sparks debates on whether investors treat a factor as risk or as an alpha opportunity. In corporate finance, discerning which factors constitute risks aids in identifying an appropriate discount rate, which is essential for determining the net present value of international projects. To our knowledge, we are among the first to explore this question in an international context.

Our empirical analysis reveals that the global CAPM wins the horse race in explaining future fund flows, outperforming other metrics such as past fund returns, the three-factor model, and the four-factor model. Global investors regard the market factor as a risk, but they tend to treat other factors, especially the value factor, as strategies for achieving outperformance. Our results are robust to using alternative estimation techniques and falsification tests using passive funds. They are also not affected by naive heuristic benchmarks such as Morningstar fund ratings or estimation errors in factor loadings. Using data on the geographic locations of global investors, we find that these results largely hold for investors everywhere.

Our findings indicate that larger institutional investors typically regard market beta as a risk factor and therefore discount fund performance attributed to market exposure. Conversely, high-net-worth individuals tend to react positively to market betas. However, it appears that none of the investor groups employ complex benchmarks for fund evaluation, as their investment flows respond positively to fund performance linked to value exposure. These results suggest that while global investors are sophisticated enough to recognize market beta risk, they seem to seek outperformance through factor-based strategies.

Last, given that the CAPM serves as a prevalent benchmark influencing fund flows, we find that the aggregate trading activities of global funds driven by CAPM-induced flows impact stock prices. Specifically, stocks that experience substantial purchases by fund managers due to CAPM-driven inflows earn a higher average alpha compared to those stocks subjected to significant sales following CAPM-driven outflows. We also find that this outperformance tends to reverse in the long run, albeit with weak significance.

We, however, do not find similar price impacts that are induced by global investors' use of either the three-factor model or the four-factor model. These results of price impacts align with demand-based asset pricing theory, which posits that flow-induced trading imposes temporary price pressures on stock prices, leading to subsequent reversals.

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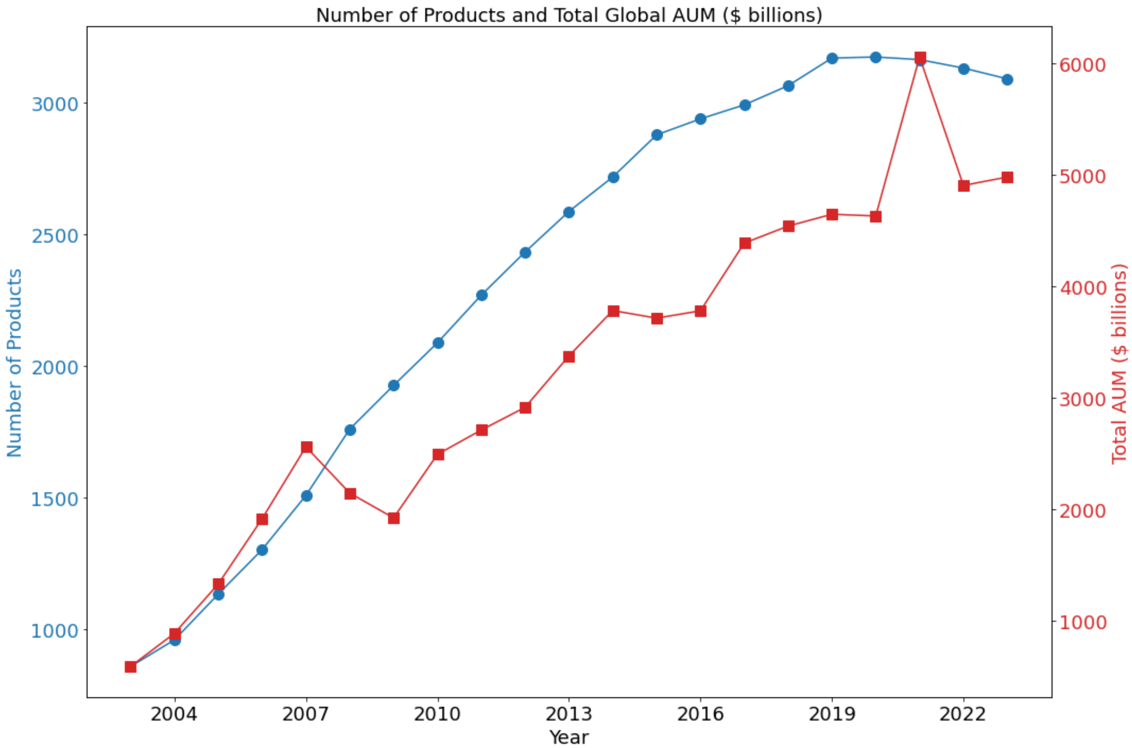
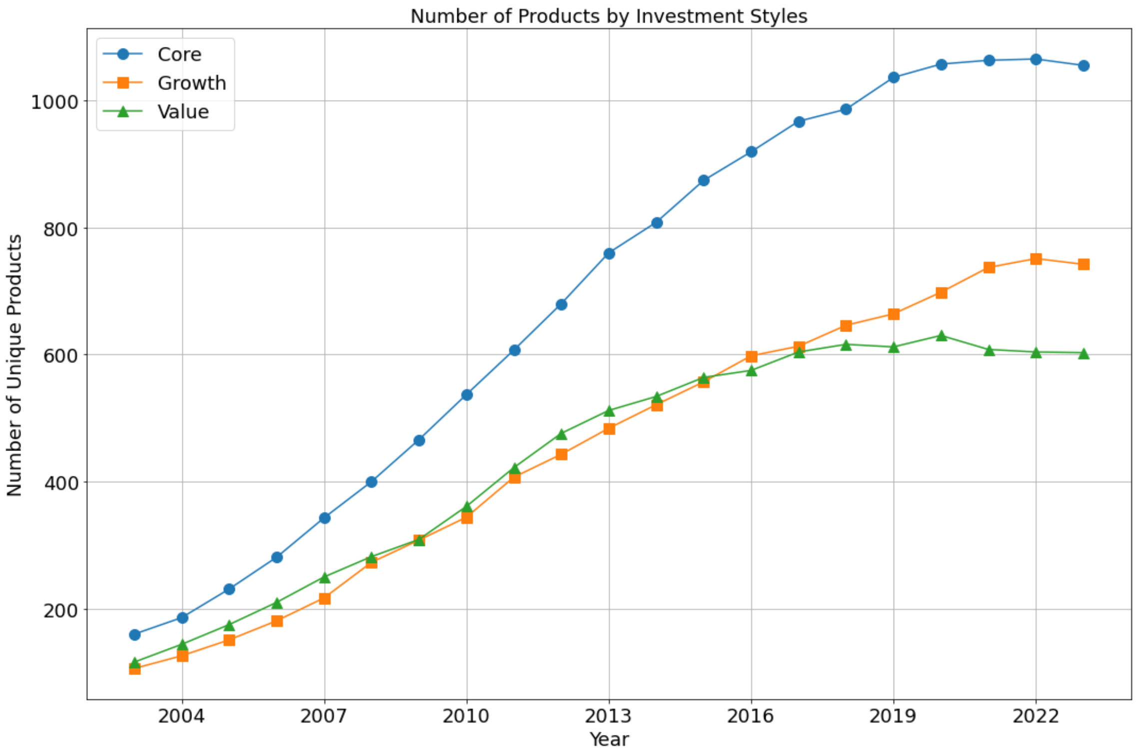
Figure 1. Number of global products and total AUM over time



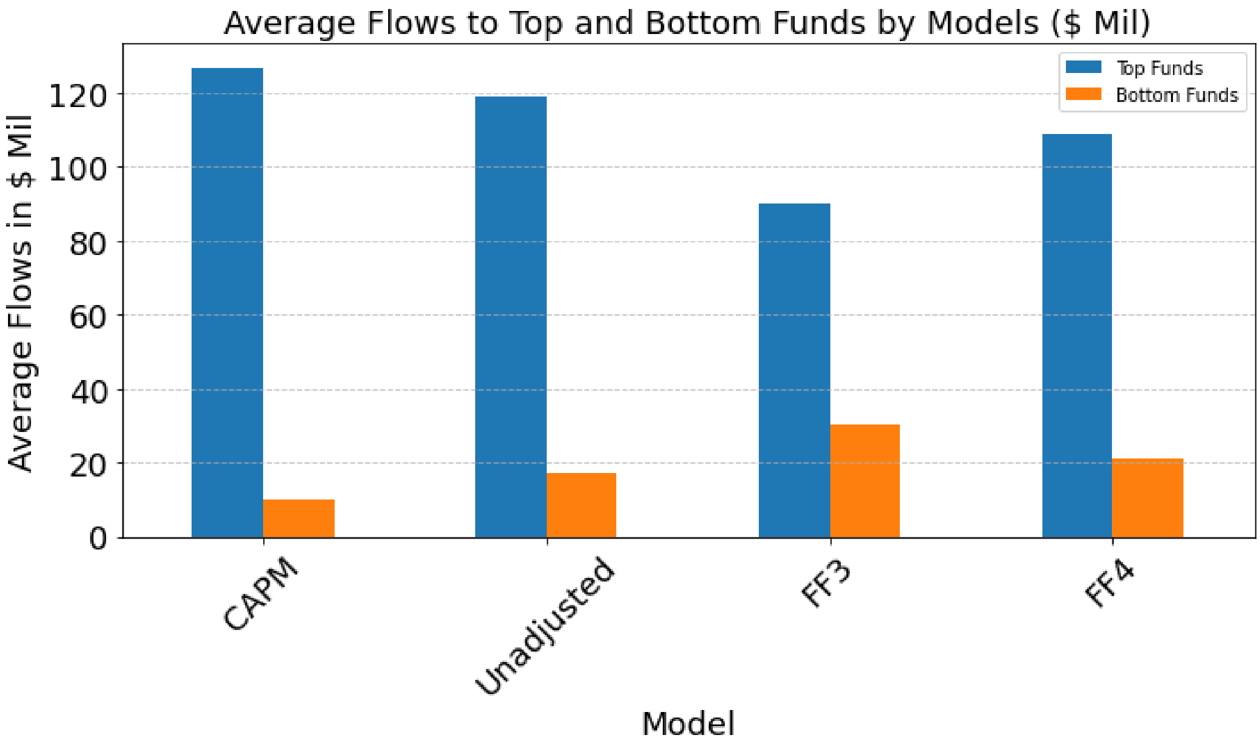
This figure depicts the annual number of unique global institutional funds (products) and the total assets under management (AUM) in billions of dollars for the period from 2003 through 2023. The blue line with circular markers indicates the number of products, corresponding to the left-hand scale, while the red line with square markers represents the AUM in billions, aligned with the right-hand scale. The sample consists of global active equity products with a mandate to invest in diversified global equities, without targeting any specific market exclusively.

Figure 2. Number of products by investment style



This figure shows the growth in the number of unique global institutional funds (products) by investment styles for the period 2003-2023. The blue line with circular markets represents the number of Core style products. The orange line with triangular markets represents the number of Growth products. The green line with the square markers represents the number of Value products. We obtain information on fund styles from Nasdaq eVestment.

Figure 3. Global flows to top-ranked and bottom-ranked funds based on competing performance metrics: Univariate evidence



This figure depicts the average dollar flows in $ million to the top-ranked funds (shown as blue bars on the left-hand-side of each model) and bottom-ranked global funds (depicted as orange bars on the right-hand-side of each model) according to various asset pricing models. "CAPM" represents the average alpha obtained from the Capital Asset Pricing Model. "Unadjusted" indicates the average return over the past month. "FF3" denotes the average alpha obtained from the three-factor model, while "FF4" represents the average alpha obtained from the four-factor model. At the end of each month, we rank and sort global funds into quintiles based on a performance metric, where the top quintile contains funds with high performance and the bottom quintile consists of funds with low performance. We then compute the one-quarter-ahead average dollar flow for each quintile. The figure shows the average dollar flow over the sample period from 2003 through 2023.

Table 1. Characteristics of global funds

Year	No. of Unique Funds	Total AUM ($m)	Mean AUM ($m)	Mean No. of Stocks in Portfolio
2003	859	594,527.1	1,509.0	55
2004	960	891,426.1	1,888.6	57
2005	1,134	1,333,390.9	2,318.9	59
2006	1,303	1,918,293.5	2,764.1	58
2007	1,509	2,563,029.9	3,033.2	59
2008	1,761	2,148,458.6	2,157.1	57
2009	1,927	1,925,969.6	1,704.4	60
2010	2,089	2,495,031.0	1,919.3	62
2011	2,270	2,713,497.7	1,811.4	63
2012	2,434	2,916,657.0	1,748.6	61
2013	2,588	3,377,319.9	1,834.5	62
2014	2,719	3,784,318.8	1,930.8	64
2015	2,879	3,716,092.4	1,774.6	61
2016	2,940	3,781,994.2	1,718.3	61
2017	2,993	4,388,847.6	1,912.4	59
2018	3,066	4,541,060.7	1,925.0	58
2019	3,171	4,647,314.4	1,907.8	56
2020	3,175	4,631,764.9	1,841.7	55
2021	3,165	6,056,484.2	2,368.6	54
2022	3,133	4,905,566.2	1,905.8	51
2023	3,092	4,980,487.3	1,952.4	49
Average	2,341.3	3,252,930.1	1,996.5	58

This table reports the annual characteristics of global institutional funds for the period 2003-2023. “No. of Unique Funds” is the total number of unique global active equity products in a given year. “Total AUM ($m)” is the total assets under management aggregated across all global products in a given year. “Mean AUM ($m)” is the average AUM across global funds computed each year. “Mean No. of Stocks in Portfolio” indicates the median number of stocks in a portfolio, averaged across products in a given year.

Table 2. Geography of global fund managers

Country	No. of Unique Funds (2003-2023)	Total AUM ($m) (2023)
Australia	57	32,111.3
Belgium	5	3,496.4
Bermuda	19	25,088.0
Brazil	19	1,468.7
Canada	157	205,728.8
Chile	4	2,275.1
Denmark	18	30,709.6
France	57	28,186.7
Germany	63	22,210.9
Guernsey	4	11,548.3
India	8	15,917.6
Ireland	24	17,777.3
Italy	4	155.1
Japan	16	24,312.4
Luxembourg	23	20,968.4
Netherlands	11	8,631.4
Norway	11	2,348.0
Saudi Arabia	3	279.7
Singapore	9	3,090.9
South Africa	25	2,445.9
South Korea	3	471.5
Spain	8	263.0
Sweden	9	1,184.1
Switzerland	85	95,007.1
United Arab Emirates	3	112.3
United Kingdom	554	859,571.5
United States	2,825	3,562,799.7

This table presents the count of unique global institutional funds (products) and the total assets under management (AUM), categorized by the domicile of asset managers across 27 countries. The last column reports the total AUM as of December 2023.

Table 3. Aggregate flows

Year	Mean Net Flow %	Mean Net Dollar Flow ($ mil)	Sum of Net Dollar Flow ($ mil)
2003	13.33	186.49	68628.54269
2004	10.72	170.67	76120.74552
2005	10.17	166.79	90399.68627
2006	10.11	186.99	123786.6181
2007	7.37	134.28	108098.0414
2008	-7.50	-215.83	-204824.9242
2009	9.03	145.81	159226.5222
2010	6.62	106.36	133263.8528
2011	0.35	-11.69	-17038.10844
2012	5.16	66.99	108860.684
2013	5.68	82.67	148315.084
2014	2.15	19.62	37414.94951
2015	1.18	-1.24	-2520.822606
2016	1.59	10.21	22020.98087
2017	5.62	78.11	175203.9539
2018	-0.99	-48.07	-110521.361
2019	3.68	48.93	116457.1239
2020	4.03	46.87	115208.8566
2021	2.98	37.48	93725.40298
2022	-4.03	-113.45	-286920.8783
2023	0.97	12.13	30378.44263
Average	4.20	52.86	46,918.26

This table reports the net capital flow into global institutional funds for each year in the period 2003-2023. Column (2) reports mean net flow in %, column (3) reports the average net dollar flow per fund, and column (4) shows total net dollar flow into all funds.

Table 4. Descriptive statistics for global funds

Panel A: Fund characteristics					
	Mean	Std. Dev	P25	Median	P75
Age	118.630	113.067	39.000	88.000	163.000
Volatility	4.737%	1.967%	3.308%	4.388%	5.818%
Net return	1.830%	0.633%	1.424%	1.680%	2.160%
Alpha (four-factor)	-0.058%	1.345%	-0.769%	-0.107%	0.461%
Market beta	1.010	0.045	0.984	0.995	1.041
Size loading	0.180	0.158	0.034	0.134	0.337
Value loading	-0.112	0.194	-0.226	-0.064	0.053
Momentum loading	0.052	0.170	-0.089	0.016	0.214
Panel B: Correlation between flows and alphas					
	Flow	CAPM alpha	3-factor alpha	4-factor alpha	Unadjusted ret.
Flow	1.00				
CAPM alpha	0.08	1.00			
3-factor alpha	0.07	0.88	1.00		
4-factor alpha	0.06	0.81	0.92	1.00	
Unadjusted return	0.01	0.48	0.41	0.42	1.00

This table reports descriptive statistics of global funds (Panel A) and the correlation matrix between fund flows and alphas (Panel B). In panel A, fund age is the number of months since the inception of a global fund (product) as dated in Nasdaq eVestment. Net return is the net-of-fee return on global funds as reported in Nasdaq eVestment. Return volatility is the standard deviation of net returns on individual funds. Market betas and loadings on individual factors are estimated using the methodology described in Appendix A. Panel B shows the correlations between next-period fund flow (%) and various measures of fund performance (the CAPM alpha, the three-factor alpha, the four-factor alpha, and unadjusted net returns on individual funds). The sample period is between 2003 and 2023.

Table 5. Horse race of competing measures of fund performance

Dep Var:	Flow (1)	Flow (2)	Flow (3)	Flow (4)	Flow (5)	Flow (6)
Unadjusted return	0.606***	-0.257	0.362**	0.354**		
	(6.820)	(-1.336)	(2.554)	(2.588)		
CAPM alpha		0.949***			0.728***	0.692***
		(4.867)			(4.175)	(4.256)
3-factor alpha			0.336**		-0.026	
			(2.215)		(-0.144)	
4-factor alpha				0.347**		0.020
				(2.460)		(0.120)
Observations	208,956	208,956	208,956	208,956	208,956	208,956
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.576	0.577	0.577	0.577	0.577	0.577

This table reports estimates from regressions of future fund flows on measures of fund performance. *Flow* is the one-month-ahead net flow (in %) into a fund. *Unadjusted return* is the fund's net-of-fee raw return. *CAPM alpha* is the fund's net-of-fee alpha from the CAPM model. *3-factor alpha* is the fund's net-of-fee alpha from the three-factor model. *4-factor alpha* is the fund's net-of-fee alpha from the four-factor model. Robust standard errors are double-clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 6. Pairwise comparisons of performance measures

	CAPM alpha vs Unadjusted Return	CAPM alpha vs 3-factor alpha	CAPM alpha vs 4-factor alpha
% of coefficients differences >0	0.800	0.889	0.822
Binomial p-value	<0.01	<0.01	<0.01
Sum of Coefficient Differences	40.132**	29.528*	26.895**
p-value	0.010	0.058	0.045

	Unadjusted Return vs 3-factor alpha	Unadjusted Return vs 4-factor alpha
% of coefficients differences >0	0.644	0.644
Binomial p-value	0.072	0.072
Sum of Coefficient Differences	4.484	3.955
p-value	0.704	0.728

	3-factor alpha vs 4-factor alpha
% of coefficients differences >0	0.556
Binomial p-value	0.551
Sum of Coefficient Differences	31.232
p-value	0.120

This table presents the pairwise comparison of asset pricing models in their abilities to predict future fund flows. For each pair of models, we estimate Equation 1 (see description in page 18). We compare coefficients for which the decile ranks are the same magnitude but the ordering is reversed (i.e., β_{ij} versus β_{ji}). The first test is whether the proportion of positive coefficient differences is greater than 0.5 (binomial p-value is reported under the proportion of positive coefficient differences). The second test is whether the summed difference $(\beta_{ij} - \beta_{ji})$ across all pairwise comparisons is equal to zero (p-value is reported under the summed difference). Panel A compares the CAPM alpha with each of the other three performance measures (unadjusted net returns, the three-factor alpha, and the four-factor alpha). Panel B compares unadjusted net returns with the three-factor alpha and the four-factor alpha. Panel C compares the three-factor alpha with the four-factor alpha.

Table 7. Flows to top funds

Dep Var:	Flow (1)	Flow (2)	Flow (3)	Flow (4)	Flow (5)	Flow (6)
UnRet_M_CAPM	-0.314**					
	(-2.562)					
UnRet_E_CAPM	1.185***					
	(8.269)					
UnRet_M_3F		0.042				
		(0.316)				
UnRet_E_3F		1.089***				
		(7.793)				
UnRet_M_4F			0.064			
			(0.490)			
UnRet_E_4F			1.078***			
			(7.762)			
CAPM_M_3F				0.267*		
				(1.899)		
CAPM_E_3F				1.156***		
				(8.455)		
CAPM_M_4F					0.268**	
					(2.043)	
CAPM_E_4F					1.167***	
					(8.524)	
3F_M_4F						0.064
						(0.474)
3F_E_4F						1.068***
						(8.117)
Observations	208,956	208,956	208,956	208,956	208,956	208,956
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.576	0.575	0.575	0.575	0.575	0.575

This table reports the results for the panel regressions of future net fund flows on indicators of pairwise performance disparities. In column (1), $UnRet\_M\_CAPM$ is the difference between Top_UnRet and Top_CAPM, where Top_UnRet (Top_CAPM) is a dummy variable equal to one if the fund's unadjusted net return (the CAPM alpha) is in the top quintile of the unadjusted net return (the CAPM alpha) distribution in a particular month, and zero otherwise. $UnRet\_E\_CAPM$ is a dummy variable equal to one if the fund belongs to the top quintile in both performance metrics. We repeat the same construction procedure for other pairs of top-ranked fund indicators: unadjusted net return versus the three-factor alpha in column (2), unadjusted return versus the four-factor alpha in column (3), CAPM alpha versus the three-factor alpha in column (4), CAPM alpha versus the four-factor alpha in column (5), and the three-factor alpha versus the four-factor alpha in column (6). Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 8. Return decomposition

	Full Sample	Different Periods		Adj NetRet		AUM		Fund Age	
Subsample:		2003-2010	2011-2023	Negative Adj NetRet	Positive Adj NetRet	Above-median AUM	Below-median AUM	Above median fund age	Below median fund age
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha	0.692***	1.299***	0.541***	0.603***	0.798***	0.906***	0.529***	0.684***	0.652***
	(7.378)	(6.316)	(5.471)	(6.498)	(7.814)	(7.438)	(5.798)	(5.976)	(6.829)
Market return	-0.128	0.109	-0.110	-0.124	-0.170	-0.088	-0.185	-0.118	-0.093
	(-0.748)	(0.493)	(-0.477)	(-0.721)	(-0.916)	(-0.410)	(-1.089)	(-0.603)	(-0.515)
Size return	0.134	1.613***	-0.469	-0.214	0.564	0.041	0.169	0.217	-0.140
	(0.452)	(2.647)	(-1.636)	(-0.706)	(1.645)	(0.104)	(0.573)	(0.600)	(-0.443)
Momentum return	0.181	-0.029	0.386	0.270	-0.077	0.338	0.029	0.132	0.227
	(0.920)	(-0.113)	(1.450)	(1.444)	(-0.367)	(1.396)	(0.150)	(0.581)	(1.101)
Value return	0.752***	0.888	0.788***	0.728***	0.718***	0.775***	0.709***	0.611***	0.862***
	(3.690)	(1.240)	(3.730)	(3.654)	(3.317)	(3.073)	(3.882)	(3.008)	(3.865)
Observations	208,956	29,705	179,251	111,683	97,273	104,621	104,335	103,611	105,345
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.577	0.613	0.557	0.577	0.596	0.600	0.557	0.605	0.558

This table reports the results for the panel regressions of next-period net fund flow on alpha and factor-related returns. *4-factor alpha* is the alpha estimated using the 4-factor model. *Market return* is the market return, *Size return* is the size-related return, *Value return* is the value-related return, and *Momentum return* is the momentum-related return. Column (1) includes the full sample. Columns (2) and (3) are sub-samples for periods 2003-2010 and 2011-2023, respectively. Columns (4) and (5) are sub-samples for funds with negative market-adjusted net return and positive market-adjusted net return, respectively. Columns (6) and (7) are sub-samples for funds with above-median AUM and below-median AUM, respectively. Columns (8) and (9) are sub-samples for funds above and below the median fund age, respectively. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 9. Geographic breakdown of investor locations and response of flows to components of fund returns

Dep Var: Flow	Asia excl. Japan	Japan	Australia	Europe	U.K.	North America	Rest of World
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.632***	0.586**	0.549***	0.585***	0.436***	0.800***	0.613***
	(3.591)	(2.446)	(2.800)	(3.673)	(2.648)	(6.417)	(3.509)
Market return	0.152	-0.638	-0.352	-0.486*	-0.215	0.079	-0.562
	(0.360)	(-1.394)	(-0.964)	(-1.771)	(-0.658)	(0.338)	(-1.340)
Size return	0.234	-0.718	-0.037	-0.616	-0.372	0.228	-0.123
	(0.378)	(-0.805)	(-0.062)	(-1.484)	(-0.714)	(0.603)	(-0.232)
Momentum return	1.024**	0.272	0.123	0.152	0.135	0.343	-0.095
	(2.258)	(0.509)	(0.295)	(0.491)	(0.399)	(1.359)	(-0.205)
Value return	-0.011	0.813**	0.610*	0.733**	0.407	0.859***	0.456
	(-0.036)	(2.098)	(1.726)	(2.533)	(1.377)	(3.392)	(1.470)
Observations	24,511	17,498	24,277	61,237	34,904	127,238	29,587
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.346	0.361	0.393	0.337	0.356	0.450	0.311

This table reports the results for the panel regressions of future net fund flow on alpha and factor-related returns, which are estimated for subsamples split based on the origins of fund flows. Columns (1)-(7) present the estimation results for flows from investors who are domiciled in Asia excluding Japan, Japan, Australia, Europe, United Kingdom, North America, and the rest of the world, respectively. *Alpha* is the alpha estimated using the four-factor model. *Market Return* is the component of a fund's performance that is traced to its exposure to the market. *Size return* is the component of fund performance that is traced to the size factor, *Value Return* is the component of fund performance that is traced to the value factor. And *Momentum Return* is the component of fund performance that is traced to the momentum factor. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 10. Global fund styles and response of flows to components of fund returns

Dep Var: Flow	Core	Growth	Value
	(1)	(2)	(3)
Alpha	0.944***	0.708***	0.594***
	(7.280)	(5.650)	(5.213)
Market return	-0.092	-0.434*	-0.054
	(-0.469)	(-1.775)	(-0.266)
Size return	0.214	0.120	0.422
	(0.527)	(0.340)	(1.037)
Momentum return	0.358	-0.154	0.090
	(1.463)	(-0.596)	(0.382)
Value return	1.034***	0.690***	0.400*
	(4.666)	(2.909)	(1.792)
Observations	84,088	56,307	58,451
Year*Month FE	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes
Adjusted R-squared	0.591	0.594	0.575

This table reports results for the panel regressions of future net fund flow on alpha and factor-related returns, which are estimated for subsamples split based on fund investment styles. Columns from (1) to (3) report results for the Core style, Growth style, and Value style, respectively. *Alpha* is the alpha estimated using the four-factor model. *Market Return* is the component of a fund's performance that is traced to its exposure to the market. *Size return* is the component of fund performance that is traced to the size factor, *Value Return* is the component of fund performance that is traced to the value factor. And *Momentum Return* is the component of fund performance that is traced to the momentum factor. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 11. Estimation error in factor loadings

In-sample versus out-of-sample factor loadings

Panel A: Beta estimates

	1 (Low)	2	3	4	5 (High)	High minus Low	Precision ratio
in-sample	0.731	0.931	1.013	1.088	1.226	0.495	
standard error	0.007	0.008	0.008	0.010	0.008		
out-of-sample	0.678	0.838	0.868	0.875	0.896	0.218	0.440
standard error	0.030	0.042	0.046	0.049	0.056		

Panel B: Size coefficients

	1 (Low)	2	3	4	5 (High)	High minus Low	Precision ratio
in-sample	-0.172	-0.012	0.110	0.280	0.602	0.774	
standard error	0.019	0.022	0.021	0.026	0.019		
out-of-sample	-0.108	-0.057	-0.006	0.096	0.290	0.398	0.515
standard error	0.039	0.045	0.050	0.058	0.073		

Panel C: Value coefficients

	1 (Low)	2	3	4	5 (High)	High minus Low	Precision ratio
in-sample	-0.580	-0.242	-0.051	0.123	0.374	0.954	
standard error	0.034	0.031	0.024	0.018	0.010		
out-of-sample	-0.178	-0.023	0.023	0.129	0.250	0.428	0.449
standard error	0.056	0.039	0.042	0.037	0.046		

Panel D: Momentum coefficients

	1 (Low)	2	3	4	5 (High)	High minus Low	Precision ratio
in-sample	-0.428	-0.144	-0.007	0.117	0.302	0.730	
standard error	0.044	0.034	0.028	0.024	0.016		
our-of-sample	-0.052	0.044	0.097	0.142	0.261	0.313	0.429
standard error	0.090	0.063	0.060	0.053	0.066		

This table reports comparisons between the in-sample and out-of-sample estimates of factor loadings. In panel A, to compute the in-sample market beta estimate, we first rank and sort funds into quintiles based on their estimated market betas at the end of each month, where quintile 1 contains funds with low average betas, while quintile 5 comprises funds with high average betas. We then calculate the average beta for each quintile at the end of the month. The first row of panel A reports the average in-sample market beta estimate across all months during the sample period, while the second row reports the associated standard error. To estimate out-of-sample market betas, as before, funds are sorted into quintiles based on market beta at the end of month t. We then calculate the average return on each quintile for month $t+1$. The out-of-sample market beta is then obtained from the regression of average returns on each quintile (in excess of risk-free rate) on the market risk premium. We report the estimated market beta from this regression in the third row and the associated standard error in the fourth row. $High-Low$ is the spread of beta estimates between quintile 5 and quintile 1. The precision ratio is the ratio of the out-of-sample spread to the in-sample spread. A higher precision ratio indicates that the out-of-sample estimate is closer to the in-sample estimate (i.e., lower estimation errors). Panel B, C, and D repeat the same procedure as in panel A for the size factor, the value factor, and the momentum factor, respectively.

Table 12. Investor types and the response of flows to components of fund returns

Dep Var: Flow	Big Mandate	Small Mandate	(1) minus (2)	High networth	Insurance	Pension	(4) minus (5)	(4) minus (6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	0.825***	0.908***	-0.083	0.563**	0.541**	0.606***	0.022	-0.043
	(4.179)	(5.890)	p=0.723	(2.264)	(2.281)	(3.119)	p=0.943	p=0.876
Market return	-0.126	0.038	-0.163	0.845	-0.477	-0.370	1.322**	1.215*
	(-0.324)	(0.092)	p=0.769	(1.551)	(-0.937)	(-0.939)	p=0.044	p=0.066
Size return	-1.900***	0.283	-2.183**	-0.548	-0.244	-0.011	-0.304	-0.538
	(-2.651)	(0.473)	p=0.021	(-0.689)	(-0.392)	(-0.018)	p=0.756	p=0.599
Momentum return	0.593	0.362	0.231	0.469	0.100	-0.109	0.369	0.578
	(1.443)	(0.826)	p= 0.681	(0.751)	(0.172)	(-0.246)	p=0.628	p=0.441
Value return	0.567**	0.662**	-0.095	0.642*	0.424	0.358	0.218	0.284
	(2.011)	(2.524)	p=0.772	(1.651)	(1.262)	(1.280)	p=0.617	p=0.461
Observations	83,489	141,189		20,508	23,752	50,368		
Year*Month FE	Yes	Yes		Yes	Yes	Yes		
Cluster by Product	Yes	Yes		Yes	Yes	Yes		
Cluster by Year*Month	Yes	Yes		Yes	Yes	Yes		
Adjusted R-squared	0.346	0.0363		0.251	0.278	0.263		

This table reports the results for the panel regressions of future net fund flow on alpha and factor-related returns, which are estimated for subsamples of various types of global investors. Columns (1) and (2) report the results for global investors with big mandates (AUM greater than $500 million) and small mandates (AUM less than $500 million), respectively. Column (3) reports the difference between the estimated coefficients in columns (1) and (2). Columns (4), (5), and (6) report the results for high-net-worth individuals, insurance providers, and pension funds, respectively. Columns (7) and (8) show the differences in coefficient estimates for insurance companies and pension funds compared to those for high-networth individuals. *Alpha* is the alpha estimated using the four-factor model. *Market Return* is the component of a fund's performance that is traced to its exposure to the market. *Size return* is the component of fund performance that is traced to the size factor, *Value Return* is the component of fund performance that is traced to the value factor. And *Momentum Return* is the component of fund performance that is traced to the momentum factor. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 13. Asset pricing implications: Flow-induced portfolios

Risk-adjustment using the 4-factor model (Alphas)	4-factor alphas					t-statistics				
Holding period =	1	12	36	48	72	1	12	36	48	72
CAPM flow-induced trades	0.94	-0.49	0.04	-0.23	-0.33	2.27	-0.88	0.23	-0.98	-1.75
3F flow-induced trades	0.24	-0.38	0.15	0.06	-0.35	1.52	-0.82	0.86	0.39	-1.82
4F flow-induced trades	0.27	-0.41	0.16	0.05	-0.37	1.75	-0.90	0.86	0.28	-1.87

Spanning tests	Alpha					t-statistics				
Holding period =	1	12	36	48	72	1	12	36	48	72
CAPM-based portf. alpha after adjusting for 3F- and 4F-based portf. returns	0.64	-0.07	-0.06	-0.25	0.07	2.22	-0.32	-0.50	-1.85	1.09
3F-based portf. alphas after adjusting for CAPM-based portf. returns	0.21	0.07	0.11	0.24	-0.13	1.56	0.31	0.89	2.24	-1.39
4F-based portf. alphas after adjusting for CAPM-based portf. returns	0.25	0.03	0.12	0.22	-0.15	1.79	0.16	0.90	2.04	-1.52

This table presents the results of portfolio tests examining the impact of flow-induced trading on global stock prices. Flow-induced trading is estimated using Equation (3) for each asset pricing model. “CAPM flow-induced trades” represents the average alpha on portfolios constructed using $FIT\_CAPM_{j,t}$ of individual stocks, which is the aggregate global fund trading induced by global investors’ use of the CAPM. “3F flow-induced trades” denotes the average alpha on portfolios constructed using $FIT\_FF3_{j,t}$ of individual stocks, which is the aggregate global fund trading induced by global investors’ use of the three-factor model. “4F flow-induced trades” represents the average alpha on portfolios constructed using $FIT\_FF4_{j,t}$ of individual stocks, which is the aggregate global fund trading induced by global investors’ use of the four-factor model. To construct the portfolios, at the end of month t, stocks are ranked and sorted into quintiles based on each of the flow-induced trading measures, which are computed at the end of month $t-1$. Portfolios are then held for various holding periods, ranging from 1 month to 72 months. We compute the difference in returns (spread) between quintile 5 (most heavily purchased stocks) and quintile 1 (most heavily sold stocks). Panel A reports the four-factor alpha obtained from the time-series regression of returns on the spread portfolio on the four-factor model.

Panel B reports the results of spanning tests in which we use returns on one portfolio to explain the return on another portfolio. The first row of panel B, for example, reports the alpha of the time-series regression of returns on the spread portfolio of $FIT\_CAPM_{j,t}$ (as obtained from panel A) against returns on the spread portfolios of $FIT\_FF3_{j,t}$ and $FIT\_FF4_{j,t}$. The second row of panel B presents the alpha from the time-series regression of returns on the spread portfolio of $FIT\_FF3_{j,t}$ against returns on the spread portfolios of $FIT\_CAPM_{j,t}$. The third row of panel B presents the alpha from the time-series regression of returns on the spread portfolio of $FIT\_FF4_{j,t}$ against returns on the spread portfolios of $FIT\_CAPM_{j,t}$. t-statistics are computed using Newey-West standard errors with 10 lags.

Appendix

A Measuring fund alphas

Our empirical analysis involves a comparison of three asset pricing models, which investors might employ to estimate alpha: the Capital Asset Pricing Model (CAPM), the Fama and French's (1993) three-factor model, and the four-factor model which additionally includes momentum as proposed by Carhart (1997). For each fund, we estimate its alpha on a monthly basis using 60-month rolling regressions. The four-factor alpha, for example, is estimated using the following rolling-window regression:

$$R_{p\tau} - R_{f\tau} = \alpha_{pt}^{4F} + \beta_{pt}(R_{m\tau} - R_{f\tau}) + s_{pt}SMB_{\tau} + h_{pt}HML_{\tau} + m_{pt}UMD_{\tau} + \epsilon_{p\tau} \quad (4)$$

where $R_{p\tau}$ is the net return on fund p in month τ. $R_{f\tau}$ is the one-month Treasury bill rate. $R_{m\tau}$ is the return on the MSCI ACWI index. SMB_{τ}, HML_{τ}, and UMD_{τ} are the size, value, and momentum factors, respectively. The global size factor is the return difference between the MSCI ACW Small Cap index and the MSCI ACW Large Cap index. The global value factor is the return difference between the MSCI ACW Value index and the MSCI ACW Growth index. The global momentum factor is the excess return on the MSCI ACW Momentum index. Having estimated the loadings on each factor, we calculate a fund's four-factor alpha in month t as the difference between realized fund returns and returns related to the fund's exposures to the market, size, value, and momentum factors in month t:

$$\hat{\alpha}_{pt}^{4F} = R_{pt} - R_{ft} - \left[\hat{\beta}_{pt}(R_{mt} - R_{ft}) + \hat{s}_{pt}SMB_t + \hat{h}_{pt}HML_t + \hat{m}_{pt}UMD_t\right] \quad (5)$$

where $\hat{\beta}_{pt}$, $\hat{s}_{pt}$, $\hat{h}_{pt}$, and $\hat{m}_{pt}$ are the estimated coefficients from Equation (4).

To account for delays in the response of flows to fund performance, we follow Barber, Huang, and Odean (2016) and accumulate fund alphas over the past 18 months using an exponential decay function as follows:

$$ALPHA_{pt}^{4F} = \frac{\sum_{s=1}^{18} e^{-\lambda(s-1)}\hat{\alpha}_{p,t-s}^{4F}}{\sum_{s=1}^{18} e^{-\lambda(s-1)}} \quad (6)$$

where $\hat{\alpha}_{p,t-s}^{4F}$ is from Equation (5) and the decay parameter $\lambda = 0.20551497$ is estimated by Barber, Huang, and Odean (2016).[28] We apply the same procedure to estimate monthly alphas from CAPM, the three-factor model, as well as the unadjusted return.

[28]Our findings do not qualitatively change if we use the equally weighted average of alphas over the past 18 months as opposed to the decay function.

B Additional results

Figure A.1. Nasdaq eVestment Partial List of Clients

This figure presents a partial list of clients of Nasdaq eVestment as of 2023, obtained from Nasdaq eVestment.

166 public pensions
169 corporate pensions
17 superannuations
85 endowments
57 foundations
136 family offices
77 insurers
48 sovereign wealth funds
59 hedge fund of funds

Australia, Bahrain, Belgium, Bermuda, Brazil, Canada, China, Denmark, Finland, Germany, Guernsey, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Kuwait, Lichtenstein, Luxembourg, Malaysia, Mauritius, Mexico, Monaco, Netherlands, New Zealand, Norway, Oman, Peru, Poland, Portugal, Qatar, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, United Arab Emirates, United Kingdom, United States, Uruguay

Last updated 04 October 2023

Partial Client List

Public Plans

Alaska Permanent Fund
Alberta Investment Management Company
CalPERS
CalSTRS
First Swedish National Pension Fund (AP1)
LGPS Central Pool
London Pensions Fund Authority
Massachusetts PRIM
National Pension Service of Korea
New York State Common Retirement Fund
Pension Fund Association of Japan
Public Institute for Social Security Kuwait

Financial Advisors

CapTrust
Jeffries Wealth Management
Lincoln Investment Advisors Group
Raymond James Alternative Investments
St. James' Place Wealth Management
UBS Financial Services

Family Offices

Bessemer Trust Company
Capricorn Investment Group
Potenza Capital
Strenta Investment Management

Corporate Pensions

AT&T
Bayerische Versorgungskammer
Boeing Company
Google
Kaiser Permanente
PGGM Investment Management
Shell Asset Management Company
UPS Group Trust

Endowments

Baylor University
Cambridge Investment Management Limited
Haverford College
University of California Board of Regents
Vanderbilt University

Insurers

Allstate Insurance Company
American Family Insurance
CIGNA
Dai-ichi Life Insurance Company
Hartford Life Insurance Company
Northwestern Investment Management Company
Zurich Financial Services

Sovereign Wealth Funds

Future Fund Board of Guardians
Korea Investment Corporation
Kuwait Investment Authority
Mumtalakat Investing for Bahrain
State Administration of Foreign Exchange (China)

Hedge Fund of Funds

Ashburton Investments
Double Eagle Capital
Hatteras Funds
SCS Financial Holdings

Foundations

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Table A.1. Alternative estimation approach: Fama-MacBeth regressions

Dep Var:	Flow	Flow	Flow	Flow	Flow	Flow
	(1)	(2)	(3)	(4)	(5)	(6)
Unadjusted return	0.373***	0.089	0.144	0.165		
	(5.18)	(0.53)	(1.21)	(1.42)		
CAPM alpha		0.572***			0.690***	0.766***
		(3.49)			(3.08)	(3.64)
3-factor alpha			0.477***		-0.068	
			(3.81)		(-0.28)	
4-factor alpha				0.451***		-0.141
				(3.75)		(-0.64)
Adjusted R-squared	0.010	0.018	0.017	0.017	0.019	0.019

This table reports the results from from the Fama-MacBeth regressions of future fund flow on measures of fund performance. *Unadjusted net return* represents funds' net-of-fee returns. *CAPM alpha* is funds' net-of-fee alphas obtained from estimating the CAPM model. *3-factor alpha* represents funds' net-of-fee alphas from the three-factor model. *4-factor alpha* is funds' net-of-fee alphas from the four-factor model. t-statistics computed using Newey-West standard errors with 10 lags are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Interpretation: The Fama-MacBeth regression approach yields results that are consistent with those obtained from cross-sectional regressions. Thus, our results are unlikely to be driven by incidental over-weightings of certain months that arise from cross-sectional regressions.

Table A.2. Placebo analysis using passive funds.

Panel A: Cross sectional regression

Dep Var:	Flow (1)	Flow (2)	Flow (3)	Flow (4)	Flow (5)	Flow (6)
Unadjusted return	-0.157	-0.638	-0.061	0.004		
	(-0.94)	(-1.21)	(-0.22)	(0.02)		
CAPM alpha		0.526			0.371	0.341
		(0.91)			(1.17)	(1.31)
3-factor alpha			-0.120		-0.516	
			(-0.33)		(-1.35)	
4-factor alpha				-0.208		-0.494
				(-0.71)		(-1.61)
Observations	13,377	13,377	13,377	13,377	13,377	13,377
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.432	0.432	0.432	0.432	0.432	0.432

Panel B: Return decomposition

	Flow (1)
4-factor alpha	-0.215
	(-1.15)
Makret return	-0.343
	(-0.76)
Size return	-0.0280
	(-0.04)
Momentum return	-0.223
	(-0.44)
Value return	0.384
	(1.12)
Observations	13,200
Year*Month FE	Yes
Cluster by Product	Yes
Cluster by Year*Month	Yes
Adjusted R-squared	0.430

This table reports the results from the regressions of future fund flow (%) on measures of performance of passive funds. In Panel A, we re-estimate the regressions of Table 5 using a sample of global passive funds. In Panel B, we re-estimate the regressions of Table 8 using a sample of global passive funds. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Interpretation: Global flows into passive funds are not influenced by performance, suggesting that our results are unlikely to be spurious.

Table A.3. Alternative explanation: Morningstar rating

Dep Var:	Flow (1)	Flow (2)	Flow (3)	Flow (4)	Flow (5)	Flow (6)
Unadjusted return	1.515***	0.189	1.153***	1.169**		
	(4.515)	(0.261)	(2.671)	(2.569)		
CAPM alpha		1.491**			1.740***	1.747***
		(2.017)			(3.233)	(3.074)
3-factor alpha			0.606		-0.103	
			(1.196)		(-0.165)	
4-factor alpha				0.569		-0.112
				(1.027)		(-0.164)
Observations	7,613	7,613	7,613	7,613	7,613	7,613
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year*Month	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.332	0.333	0.332	0.332	0.333	0.333

This table reports the results from the regressions of future fund flows on measures of performance using the subsample of global active funds before 2004. We re-estimate the regressions of Table 5. Robust standard errors are clustered by year-month and fund, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Interpretation: Using the sample of global active funds before 2004 when Morningstar ratings were not available for institutional products, we obtain consistent results, suggesting that Morningstar ratings are unlikely to affect our findings.

Table A.4. Return Decomposition: Fama-MacBeth regression approach

Dep Var: Flow	Full sample	Before 2010	After 2010
	(1)	(2)	(3)
4-factor alpha	1.200***	1.592***	0.918***
	(9.13)	(7.30)	(8.21)
Market return	0.624	0.131	0.776
	(0.86)	(0.21)	(1.27)
Size return	1.737**	2.673***	0.283
	(2.05)	(2.88)	(0.53)
Momentum return	1.809***	1.101	1.852***
	(2.74)	(1.62)	(2.97)
Value return	1.929*	3.405*	1.393**
	(1.68)	(1.95)	(2.23)
Adjusted R-squared	0.077	0.072	0.079

This table reports the results from the Fama-MacBeth regressions of future net fund flows on alpha and factor-related returns. Specifically, we re-estimate the regressions of Table 8 but using the Fama-MacBeth approach. t-statistics computed using Newey-West standard errors with 10 lags are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Interpretation: The Fama-MacBeth regression approach yields results consistent with those obtained from Table 8, suggesting that our findings are unlikely to be driven by incidental overweightings of certain months that arise from cross-sectional regressions.