Remeasuring Scale in Active Management*

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Abstract

We argue at least 65% more total assets should be included in estimating scale of actively managed portfolios. By merging two major datasets on institutional products, we identify trillions of institutional assets that are managed under the same investment strategy as their twin mutual funds with an average return correlation of 99.9%. Overlooking the assets under management for institutional products skews crucial estimates in asset management research. We show that after including these assets in the scale metric reduces fund-level (industry-level) diminishing returns to scale of mutual funds by up to 90% (50%), suggesting a larger capacity of active asset management than the literature believed. We also observe that dollar value added of active strategies is more substantial and persistent than past assessments suggested.

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1 Introduction

Since the seminal work of Berk and Green (2004), a large empirical literature has been devoted to estimating the relationship between mutual fund scale and return performance (e.g., Chen et al., 2004; Pástor et al., 2015; Zhu, 2018; Harvey and Liu, 2021; Reuter and Zitzewitz, 2021). Scale has also become a standard control variable in various studies examining mutual fund performance, managerial skill, and trading behaviors (Pollet and Wilson, 2008; Berk and Van Binsbergen, 2015; Pástor et al., 2020; Song, 2020; Roussanov et al., 2020; Kaniel et al., 2023). Accurately measuring scale is crucial not only for asset management but also for assessing overall financial stability: holdings by equity mutual funds can lead to fire sales risks (Coval and Stafford, 2007) and externalities (Chernenko and Sunderam, 2020), influence return volatility (Greenwood and Thesmar, 2011), and heighten liquidity risks in times of crisis (Fricke and Wilke, 2023).

In this paper, we argue that at least 65% more total assets should be included in the scale metric when studying the relationship between scale, skill, and performance of actively managed portfolios. Specifically, by integrating two major datasets on institutional investment products, we discover that, on average, over half of active equity mutual funds in any given year have corresponding "twin" institutional vehicles (IVs). These are offered to institutional investors in the forms of separately managed accounts (SMAs), collective investment trusts (CITs), or commingled funds (CFs).[1] These IVs are managed using the same investment strategy as their twin mutual funds, exhibiting a return correlation higher than 99% (averaging at 99.9%).[2] When our sample starts in 1995, the twin IVs

[1]Note that SMAs, CITs, and CFs are different from institutional shareclasses of mutual funds. The academic literature has used names such as 'asset manager funds' (Gerakos et al., 2021) and 'products' (Busse et al., 2010) for these institutional portfolios that are not mutual funds.

[2]For an IV to be identified as the twin of a mutual fund, we require at least 99% return correlation between the IV and its mutual fund counterpart. Evans and Fahlenbrach (2012) require the return

managed assets amounting to 25% of the total active equity mutual fund assets. This figure escalated to about 66% by 2008 and has remained stable since. When our sample ends in 2023, the assets in the twin IVs have reached $3.37 trillion, representing 65.8% of the total active equity mutual fund assets.

It is evident that assets in these twin IVs have a significant impact on security choice and asset allocation, generate price impact, and incur transaction costs. All these factors cumulatively influence the overall strategy-level performance, which in turn affects the performance of mutual funds, as they are one of the vehicles executing the same investment strategy. Consequently, when examining the relationship between scale and various elements such as managerial skill, trading activities, or the return performance of active management, it is imperative to include these trillions in institutional assets within the scale metric.[3]

Omitting assets under management from twin IVs can severely skew crucial estimates and lead to misleading conclusions. As a starting point, we provide evidence that this oversight leads to an overestimation of the capacity for active management and an underestimation of the value added by active funds' portfolio managers. We demonstrates that estimates on diminishing return to scale are significantly inflated. When incorporating the AuM from twin IVs into the scale metric, we uncover that the negative relationship between scale and performance is overstated by up to 90% at the fund level, and approximately 50% at the industry level (Pástor et al., 2015; Zhu, 2018), revealing a substantial underestimation of the actual capacity for active management. Furthermore, by integrat-

correlation to be 95% for twin status.

[3]We acknowledge that IVs and mutual funds exhibit differences in areas such as managerial fiduciary duty, flow sensitivity, and shareholder activism levels. However, our primary focus is on the influence of twin IV assets on mutual fund trading and return performance, given that these IVs adhere to the identical investment strategy as their corresponding mutual funds.

ing twin IV assets, we ascertain that active portfolio managers possess much larger dollar value added than previously estimated; we also show that dollar value added has much greater persistence, reinforcing the argument that portfolio managers have the skill to generate substantial returns from financial markets (Berk and Van Binsbergen, 2015).

Although our analysis focuses on demonstrating the significance of accurate scale measurement through two specific examples, the pervasive nature of this measurement issue extends beyond the realm of active equity mutual funds. For instance, our findings suggest that the flow metrics utilized in some previous studies might not be comprehensive. This measurement issue extends beyond active equity mutual funds and likely affects fixed-income mutual funds and passive investment vehicles as well. As an example, Chinco and Sammon (2023) infer that passive ownership was double the total share of index mutual funds and ETFs in 2021 based on trading volume. We find that a significant portion of the "missing" passive shares are actually held in passive institutional products.[4]

This paper is organized in two parts. In the first part, we detail our data sources, with a particular focus on how we establish the connection between mutual funds and their twin IVs. Our data on IVs is primarily sourced from Morningstar and eVestment, which are two of the major data providers on institutional investment products.[5] Because neither database is comprehensive in terms of coverage, we combine the two databases to identify as many as possible of the twin IVs of mutual funds. Morningstar employs a unique strategy identifier, the Morningstar Strategy ID, which links mutual fund share classes to IVs adhering to the same investment strategy. Similarly, eVestment provides a linkage connecting separately managed accounts, collective investment trusts, or commingled

[4]Across our sample period from 1995 to 2023, passive institutional products, on average, manage assets equivalent to 80% of the total assets of passive mutual funds and ETFs (see Appendix B).

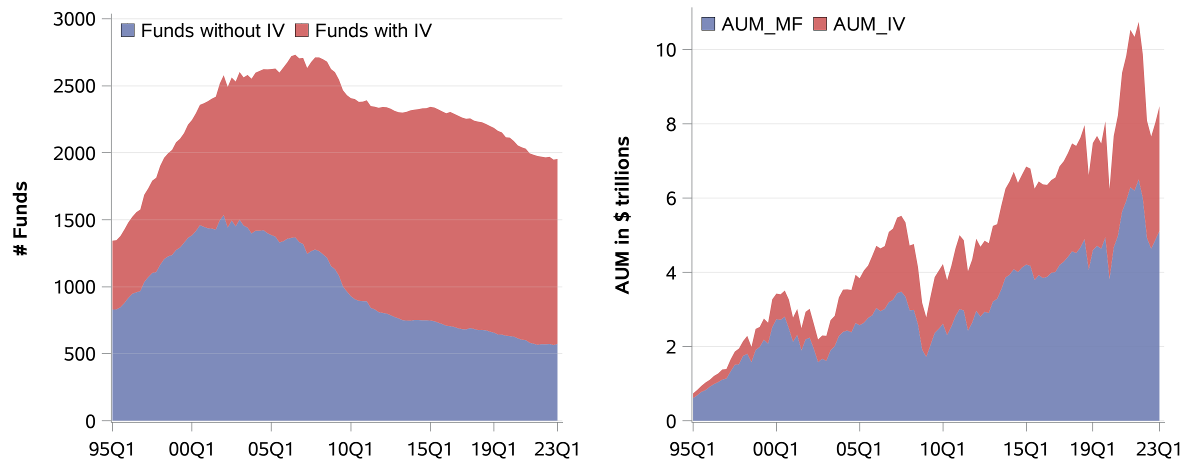
[5]Another notable data source is Informa Investment Solutions (IIS), which is used by Busse et al. (2010). Gerakos et al. (2021) obtain data from a global consulting firm without name disclosed.

funds to their mutual fund equivalents. This allows us to connect mutual funds with their twin IVs.

Because institutional clients can request specific portfolio restrictions or adjustments, IVs managed under the same strategy by the same managers may exhibit slightly varied portfolio compositions (Del Guercio and Tkac, 2002; Busse et al., 2010). To ensure we accurately capture "identical" IV-mutual fund twins, *we require the IVs to have at least 99% return correlation with their twin mutual funds over the entire history.* This conservative approach results in an average return correlation between mutual fund-IV twins that is comparable to the average pairwise return correlation among different share classes of the same mutual fund (0.999 vs. 0.999). Furthermore, the average difference in gross returns between mutual fund-IV twins is actually smaller than the range in gross returns across different share classes of the same mutual fund. Researchers often aggregate assets from various share classes of a mutual fund, recognizing that they adhere to the same investment strategy. In this sense, the twin institutional assets should also be included in order to get the complete scale metric of an active strategy.

Figure 1 delineates the number and total assets of actively managed equity mutual funds in Morningstar Direct,[6] along with the subset of those funds for which twin IVs have been identified using either the Morningstar or eVestment databases. At the start of our sample period in 1995, 549 out of 1428 active equity mutual funds in Morningstar Direct have IVs identified, adhering to the 99% return correlation criteria. These IVs collectively manage $210 billion in assets, which is 25% of the total assets managed by active equity mutual funds. By the end of our sample in 2023, 1379 out of the 1954 active equity mutual funds have twin IVs identified. These twin IVs collectively manage $3.37

[6] A mutual fund enters our sample only after its AUM exceeds $15 million.



(a) # Funds (b) AUM

Figure 1: **Summary of active equity mutual funds and twin IVs.** Panel (a) plots the number of active equity mutual funds with and without IVs identified in each quarter. Panel (b) plots the aggregate AUM of mutual funds and aggregate AUM of the twin IVs. The sample period is from Q1 1995 to Q1 2023.

trillion in assets, accounting for 65.8% of the total assets managed by active equity mutual funds. On average, during the years 1995 to 2023, approximately 56% of mutual funds meet the criteria for having twin IVs based on the 99% return correlation threshold. It is important to note that our estimates of twin IV assets are likely conservative, considering the stringent nature of this correlation requirement.

Beyond their substantial size, our analysis reveals a high correlation between the assets in these IVs and those in their twin mutual funds. This correlation underscores the importance of including institutional assets to obtain an unbiased estimate of the impact of scale on managerial skill, trading behaviors, and the return performance of active mutual funds. In addition, we observe that IV flows exhibit a lower responsiveness to past performance compared to mutual fund flows. Notably, the flow-performance sensitivity of IVs remains relatively stable, regardless of overall market conditions. This finding is in contrast to the well-documented hump-shaped mutual fund flow-performance sensitivity, as described in the work of Franzoni and Schmalz (2017).

In the second part of the paper, we examine two critical estimates from the literature to highlight the crucial role of precise scale measurement in the context of active management. We first revisit the analysis of diminishing returns to scale (DRS) in active equity mutual funds. In particular, we use the fixed-effect regression and the recursive demean approach pioneered by Pástor et al. (2015) and further refined by Zhu (2018) to estimate both fund-level and industry-level DRS.[7] Given the high correlation between institutional and mutual fund assets, our analysis reveals that using the dollar AUM of mutual funds alone in the regression can lead to an overestimation of fund-level DRS by as much as 90%. On the other hand, when fund size is represented by its logarithm, the estimated magnitude of fund-level DRS happens to be much less impacted. Moreover, as the aggregate size of mutual funds (relative to the aggregate market) and aggregate AUMs of the twin IVs are also closely related, we find that industry-level DRS is over-estimated by as much as 50%. These results suggest that the capacity for active asset management is greater than previously estimated.

Additionally, performance at the strategy level is shaped by assets from both mutual funds and twin IVs. Thus, the dollar value added, as originally estimated by Berk and Van Binsbergen (2015) using only mutual fund assets, is unlikely to be accurate. We re-calculate the dollar value added at the strategy level, incorporating the assets in twin IVs alongside those of mutual funds. Our revised estimation shows that the average dollar value added over fund-quarter observations increases from \$0.58 million, when considering only mutual fund assets, to \$1.71 million with the inclusion of twin IV assets. In other words, the dollar value added by active portfolio managers is significantly underestimated without the twin IV assets. Furthermore, our findings suggest that the persistence of

[7] Specifically, Pástor et al. (2015) propose a novel two-stage recursive demean (RD) procedure that avoids finite-sample bias in regressions with fund fixed effects, and Zhu (2018) refines the RD procedure.

dollar value added is greater than previously reported. This aligns with our finding that the capacity for active asset management is actually more substantial than earlier estimates have suggested.

Our paper contributes to the extensive literature analyzing the relationship between mutual fund scale, skill, and performance. Earlier studies include Chen et al. (2004), Yan (2008), Elton et al. (2012), Ferreira et al. (2013) among many others. Later on, researchers have tried to improve the econometric methods (e.g., Pástor et al., 2015; Zhu, 2018; Harvey and Liu, 2021), exploit exogenous changes in fund size (Reuter and Zitzewitz, 2021), or estimate DRS through structural models (Roussanov et al., 2020). Diverging from previous work, our study proposes a reevaluation of the scale metric used in the analysis of active management. We argue that an accurate assessment of scale's influence on performance necessitates the integration of both institutional and retail AUM under the same investment strategy.

Our paper is also related to the growing literature that studies institutional investment products. Some early notable studies are Del Guercio and Tkac (2002), Busse et al. (2010), Evans and Fahlenbrach (2012), Elton et al. (2014), and Jenkinson et al. (2016). More recently, Gerakos et al. (2021) conduct a comprehensive analysis on the performance of institutional products, and Jones et al. (2022) compare performance of institutional products and mutual funds and study the outcome to institutional investors in selecting institutional products. Evans et al. (2022) analyze diseconomy of scale for institutional separate accounts that utilize quantitative or fundamental investment approach. our paper diverges from these studies by highlighting the significant implications that institutional assets hold for drawing accurate conclusions about mutual funds. We underscore the importance of considering both retail and institutional AUM under the same strategy to truly understand mutual fund scale and its impact.

The rest of the paper is organized as follows. Section 2 provides the background of institutional investment vehicles. Section 3 describes in detail the data source and how we link IVs to mutual funds under the same strategy. Section 4 shows a large part of assets should be included in measuring scale of active management. Section 5 and Section 6 reexamine the relationship between scale and subsequent performance of mutual funds and dollar value added of mutual funds, respectively. Section 7 concludes. Additional results are reported in the appendices.

2 Background

Mutual funds aggregate capital from numerous investors, each possessing shares in the fund rather than direct ownership of the fund's underlying assets. In contrast, institutional products are often offered in the form of separately managed accounts (SMAs), collective investment trusts (CITs), or commingled/collective funds (CFs). SMAs are customized for a single investor, entailing direct ownership of the underlying assets, often through a custodian. CITs and CFs combine assets from multiple institutional investors, such as pension funds, endowments, and other large investment entities. For simplicity, we recognize SMAs, CITs, and CFs as institutional vehicles (IVs).

Mutual funds are primarily targeted towards retail investors. At the end of 2022, households held 89% of US mutual fund assets (ICI Fact Book, 2023). In contrast, IVs predominantly cater to institutional investors and affluent individuals.[8] The Investment

[8]There are instances where institutional investors prefer mutual funds over IVs, especially when the convenience offered by a mutual fund supersedes the benefits of customization. Mutual funds avoid exposing investors to the administrative costs involved in setting up an account, which include custodian interactions, legal formalities, audits, and for foreign investments, liaising with market authorities, tax consultants, and regulatory bodies. Smaller institutional investors might deem these administrative expenses prohibitive, leading them to opt for mutual funds.

Company Act of 1940 mandates that mutual funds must daily price their shares and disclose their performance to their investors. In stark contrast, there is no equivalent obligation for institutional investment products at large. In fact, the disclosure practices of IVs, excluding institutional mutual funds, closely resemble those of hedge funds. As a means to attract investments, institutional products proactively report periodic performance data to investment consultants and select commercial data vendors, among which Morningstar and eVestment own the largest databases of institutional investment products/strategies. These avenues have consistently stood as the primary sources of data within this sector.

In their reporting, managers of institutional products adhere to the Global Investment Performance Standards (GIPS; for the latest edition, see CFA Institute, 2020). GIPS requires that managers handling multiple portfolios with same investment strategies present their performance within a unified composite index, reflecting the weighted average performance of its constituent portfolios. Essentially, management firms report as an institutional product the pool of individual customer accounts managed by the same management team and following the same strategy. In contrast, mutual fund performance data is accessible at a more granular level (share class).

According to practitioners, equivalent investment vehicles are often created when a mutual fund or an IV demonstrates commendable performance. Under such circumstances, managers design a closely analogous product to cater to a distinct clientele. For instance, an IV can be derived from a consistently outperforming mutual fund or vice versa. These paired entities are commonly referred to as "twins."

Practitioners concur that performance differences between twin investment vehicles are generally minimal, largely due to their sharing the same portfolio manager and investment strategy, as well as legal implications related to significant performance deviations (Evans and Fahlenbrach, 2012). Nevertheless, achieving complete uniformity in performance is not entirely feasible. Certain portfolio managers might accept transitory variations in portfolio composition between twins if it bolsters the performance of one investment vehicle without detrimentally impacting the other.

In our research, aiming to accurately capture institutional assets that adhere to identical investment strategies, we have set a stringent benchmark: *Institutional vehicles must demonstrate a minimum of 99% return correlation with their corresponding twin mutual funds over the entire history.* The methodology used to identify these twin IVs of mutual funds will be detailed in the following section.

3 Link mutual funds and institutional vehicles

In this section, we describe the data source and how we link IVs to mutual funds under the same investment strategy.

3.1 Data source

Our analysis is based on three datasets from two data vendors: Morningstar mutual fund dataset, Morningstar institutional product dataset, and eVestment institutional product dataset. Recognizing that neither database of institutional products provides exhaustive coverage, we intergrate the two in order to identify the broadest possible range of twin IVs corresponding to mutual funds. Our sample period is from 1995 to the first quarter of 2023, and we explain those datasets in detail below.

We obtain survivorship bias-free data on the US domestic equity mutual funds from Morningstar Direct. The database reports mutual fund returns and fund characteristics at the level of each fund share class. We combine multiple share classes of the same mutual fund into a single fund by taking the weighted averages over fund returns and characteristics, using the assets of share classes as weights.

To construct our sample of actively managed equity mutual funds, we follow a multi-step procedure. Initially, we select U.S. equity funds from the Morningstar Direct database based on their classification within the Morningstar category. Next, we follow Pástor et al. (2015) to remove passive funds by excluding funds flagged as index funds in Morningstar or funds whose name contains "Index." Furthermore, we establish a minimum threshold for fund inclusion: a fund is only added to our sample if its AUM exceed $15 million in 2023 Q1 dollars.[9] Once a fund is included in our sample, it is retained for analysis irrespective of any subsequent changes in its AUM.

To achieve the maximum coverage of institutional vehicles, we use both the Morningstar institutional product database and the institutional product database from eVestment. The Morningstar database has been used by, for example, Evans and Fahlenbrach (2012), Elton et al. (2014), and Evans et al. (2022). The eVestment database is relatively new and has been used by, for example, Jenkinson et al. (2016) and Jones et al. (2022). By integrating these two prominent sources, we aim to capture the most complete and accurate representation of the IV landscape.

The datasets sourced from Morningstar and eVestment are of high quality and largely reliable. According to information from the Morningstar website, a significant majority (90%) of the institutional products listed in their database are from firms compliant with the Association for Investment Management and Research (AIMR) standards. This compliance framework ensures consistent and standardized reporting practices. Additionally,

[9] This threshold is set to omit very small mutual funds, and we find that our results are robust to this criterion.

based on our conversation with eVestment, eVestment also has an internal process to identify possible manager input errors. Furthermore, the reports of institutional products submitted by asset managers to eVestment align with their public disclosures, such as client reports and information available on their websites.

3.2 Linking IVs with mutual funds

We now detail our methodology for identifying twin IVs of mutual funds. The linkage of mutual funds and IVs in the Morningstar institutional product database is conducted through the Morningstar identifier "Morningstar StrategyID."[10] Morningstar elaborates on the construction of the StrategyID as follows: *"The Morningstar identifier that links investments that follow the same investment process. Often investment management companies subadvise more than one mutual fund, and offer equivalent investment pools in separate accounts, collective investment trusts, or other vehicles. Following industry convention, Morningstar groups these substantively identical pools into a single strategy. Morningstar identifies strategies through surveying management companies, as well as performing quantitative and qualitative analysis."*

Similarly, eVestment's database for each product or strategy includes a listing of various forms of investment vehicles, such as SMAs, CFs, CITs, and mutual fund share classes. This comprehensive listing enables us to effectively pair mutual funds with their corresponding IVs that are managed under the same investment strategy.

To maximize the identification of twin IVs for mutual funds, we integrate data from both Morningstar and eVestment. Notably, there are cases where mutual funds have corresponding IVs listed in both databases. Given that our mutual fund data originates

[10] Jones et al. (2022) also use Morningstar Strategy ID to identify mutual fund and IV twins. They report the median return correlations between the twins to be 99.88%.

from Morningstar Direct and considering Morningstar's widespread recognition and use in academic research, we give precedence to the information reported in the Morningstar institutional product database. We resort to the eVestment database only in instances where the necessary information is absent or incomplete in the Morningstar database.

Because institutional clients can request various portfolio restrictions or adjustments, IVs can have slightly different portfolio compositions even though they are managed by the same manager using the same strategy (Del Guercio and Tkac, 2002; Busse et al., 2010). To ensure a conservative and accurate measure when matching twin institutional assets, we establish a criterion that IVs must demonstrate at least a 99% return correlation with their corresponding mutual funds. This requirement is more stringent than that in Evans and Fahlenbrach (2012), which classifies twins with a minimum return correlation of 95%. The appendix provides more details of the matching process.

It is of interest to compare mutual funds with and without twin IVs. Table 1 presents such comparative information. We find that larger mutual funds are more likely to be associated with twin IV. For example, the average AUM of mutual funds with IV offered is $4429 million, while the average AUM of mutual funds without IV offered is only $1339 million. However, when it comes to fund families, those with and without institutional products show a similar scale in terms of total AUM. In addition, we find tht mutual funds with IVs offered typically charge lower expense ratio to the mutual fund investors.

[INSERT TABLE 1 HERE]

An additional noteworthy pattern evident in Table 1 is that mutual funds with IVs offered outperform other mutual funds by about 24 to 32 basis points (bps) per quarter. In Appendix Table C.1, we further evaluate performance of the aggregate portfolio of mutual funds with and without twin IV offered using factor models. The aggregate portfolio of mutual funds without IV twins significantly underperfom the aggregate portfolio of mutual funds with twin IVs, both before and after accounting for fees. This finding is consistent with Evans and Fahlenbrach (2012), who find that retail mutual funds with institutional twins outperform other retail mutual funds. It is also consistent with Gerakos et al. (2021), who find that institutional products outperform mutual funds on average.

To delve deeper into the characteristics of mutual funds that typically offer twin IVs, we conduct an analysis using a logit model. This model estimates the probability of a mutual fund offering an IV, taking into account various attributes of the mutual fund and its fund family. The results of this analysis are presented in Table 2.

[INSERT TABLE 2 HERE]

Our findings indicate that certain characteristics increase the likelihood of a mutual fund offering an IV. Specifically, larger mutual funds, those that have recently outperformed their benchmarks, funds characterized by lower volatility, and relatively younger funds are more inclined to offer institutional products. In addition, if a mutual fund is part of a family that has previously offered IVs, it is more likely for that mutual fund to also offer an IV.

3.3 Return Comovement between Mutual Fund and Twin IV

We place a strong emphasis on ensuring that the identified IVs are managed in the same way as their twin mutual funds. To validate the matching of IV-mutual fund twins, Table 3 compares the return correlation between IV-mutual fund twins with the average pairwise return correlation observed among share classes of the same mutual fund. We find that the average return correlation between mutual fund-IV twin (0.999) is similar to the average pairwise correlation between share classes within the same mutual funds

(0.999). Moreover, the median return correlation between IV-mutual fund twins reaches 100%, indicating nearly identical return movements between these paired entities.

[INSERT TABLE 3 HERE]

To further contextualize the level of return correlation observed between IV-mutual fund twins, we also analyze the distribution of pairwise correlations among mutual funds within the same Morningstar category, as well as those within the same category and offered by the same fund family. The average correlation among mutual funds within the same category is 0.89, and it increases to 0.938 for mutual funds within the same category and belonging to the same fund family. When compared to these figures, the return correlation between IV-mutual fund twins, which is close to or at 100%, is significantly higher. Such a high degree of correlation reinforces the premise that these twins are not only nominally linked but also managed under the same strategy.

We further evaluate the differences in gross returns between mutual funds and their corresponding twin IVs. Panel A of Figure 2 plots the cumulative benchmark-adjusted gross returns of IVs and mutual funds across all the mutual fund-IV twin pairs. Throughout our 28-year sample period, we observe that the average quarterly return difference between the mutual fund-IV twins is a mere 1.7 basis points (bps). This finding aligns with the minimal return difference between mutual fund-IV twins reported by Jones et al. (2022), who also use Morningstar Strategy ID for matching mutual funds with their twin IVs. For example, their Table 9 indicates an average gross-fee return difference of about 2.5 bps per quarter between equity mutual funds and their twin IVs.[11]

[INSERT FIGURE 2 HERE]

[11] It is noteworthy that Jones et al. (2022) do not apply the 99% return correlation threshold in their study.

Panel B of Figure 2 further shows that, for most quarters within our sample period, the average difference in gross returns between mutual fund-IV twins is, in fact, smaller than the average range of gross return differences among different share classes of the same mutual fund.

In the field of mutual fund research, aggregating the assets of different share classes from the same mutual fund is a standard practice among researchers. This approach is based on the understanding that these share classes are generally managed collectively. Consistent with this principle, it is equally important to include the assets of twin IVs in the measurement of scale. These twin IVs are managed in tandem with their mutual fund counterparts, making their assets a relevant and significant component of the overall scale.

We also acknowledge that IVs and mutual funds exhibit differences, encompassing aspects like managerial fiduciary duty, sensitivity of flows to returns, and the level of shareholder activism. However, since our primary focus is on the influence of twin IV assets on fund trading and return performance, recognizing and incorporating the assets of these twin IVs ensures a more accurate and comprehensive assessment of the fund's scale, reflecting the true scope of assets managed under the same investment strategy.[12]

In the next section, we will tabulate the assets in these twin IVs and study the relationship between mutual fund assets and twin IV assets.

[12]Because these twin IVs adhere to the same investment strategy as their corresponding mutual funds, their assets significantly determine security selection and asset allocation, and incur price impact and transaction costs.

4 Remeasuring scale in active management

In this section, we demonstrate that a significant portion of assets—specifically, at least 65% more than currently accounted for—should be included to accurately measure the scale of active management. In addition, we compare assets and flows between mutual funds and twin IVs.

4.1 Measuring assets of twin IVs

We start by documenting the total assets managed by the twin IVs of mutual funds in our sample. Columns (1) and (2) of Table 4 provide the count of active equity mutual funds listed in Morningstar Direct and the corresponding total assets in these funds at the end of each year. Columns (3) to (5) summarize the segment of these active equity mutual funds that have twin IVs, as identified within the Morningstar institutional product database. Columns (6) to (8) show the subset of mutual funds with twin IVs identified through the eVestment database. The comprehensive data combining both databases is presented in columns (9) to (11), showcasing mutual funds with twin IVs identified by either Morningstar or eVestment.

This combination of Morningstar and eVestment databases notably increases the coverage of institutional assets. Specifically, we observe an approximate 15% to 20% enhancement in coverage compared to relying on each database individually. As outlined in Section 3.2, our approach prioritizes institutional assets information from the Morningstar database. In cases where this data is unavailable, we supplement our analysis with the assets reported in the eVestment database.

[INSERT TABLE 4 HERE]

At the onset of our sample in 1995, out of 1428 actively managed equity mutual funds in Morningstar Direct, 549 had twin IVs identified, meeting the 99% return correlation criterion. These IVs collectively managed assets totaling $210 billion, representing 25% of the total assets under management by active equity mutual funds. Over time, this proportion has shown a steady increase, reaching approximately 66% by 2008 and maintaining relative stability thereafter. By the conclusion of our sample in 2023, 1379 out of 1954 active equity mutual funds have twin IVs identified, adhering to the same return correlation threshold. These IVs manage a significant $3.37 trillion in assets, accounting for 65.8% of the total assets managed by active equity mutual funds. Averaging across the sample period, we observe that 56.4% of active equity mutual funds have twin institutional investment vehicles. These twin assets are managed together with their mutual fund counterparts and thus should be included in the scale measure if one intends to understand the influence of scale on return performance.

[INSERT FIGURE 3 HERE]

Figure 3 further shows the total assets managed by equity mutual funds and the total assets managed by their twin IVs across various Morningstar categories. One can see that the twin IV assets are comparable to mutual fund assets in all the 3×3 size and value categories. In the sector funds category, the assets in IVs are relatively smaller. In short, the takeaway from Figure 3 is that fund scale should be remeasured across all the categories.

4.2 Comparing scale and flows of mutual fund-IV twins

In this section, we compare assets, flows, and flow-performance sensitivities between mutual funds and their twin IVs.

Our first line of analysis investigates the correlation between assets in mutual funds and those in their corresponding twin IVs. Panel A of Table 5 illustrates this relationship, indicating a strong correlation between assets managed under the same investment strategy. Specifically, one dollar increase in mutual fund asset is, on average, associated with 0.66 dollar increase in the twin IV assets. Further, mutual fund assets alone can explain about 55% variation in the twin institutional assets. Together with fund fixed effects, mutual fund assets can explain close to 86% variation in the twin IV assets. Additionally, we observe a meaningful association between the dollar flows into mutual funds and the corresponding flows into their twin IVs. While this relationship is highly significant, the R^2 value is comparatively lower.

[**INSERT TABLE 5 HERE**]

Following Pástor et al. (2015), we also measure the industry size of mutual funds and their twin IVs by the total mutual fund assets and the total twin IV assets as a fraction of the total stock market capitalization, respectively. Panel B of Table 5 reports the relationship between these industry size metrics for mutual funds and their twin IVs. Similar to the fund-level findings, the two industry size measures are highly correlated, albeit with a marginally lower R^2 value of 48.7%. Additionally, we find a significant correlation between the industry-level dollar flows of mutual funds and the aggregate dollar flows into their twin IVs.

Because mutual fund assets and twin IV assets are highly correlated at both the fund level and the industry level, we expect that the estimates of scale-performance relationship of active equity mutual funds in prior studies suffer from the standard omitted variable bias and thus are likely to be inaccurate. We show that this is indeed the case in Sections 5 and 6.

[**INSERT TABLE 6 HERE**]

In Table 6, we further explore how mutual fund flows and IV flows respond to past performance. Our findings indicate that while IV flows do react positively to past performance, their responsiveness is less pronounced than that of mutual fund flows. This observation aligns with the findings of Evans and Fahlenbrach (2012), who note a similar trend in the responsiveness of institutional flows.

Intriguingly, we also observe that the flow-performance sensitivity of IVs remains relatively stable regardless of overall market conditions. This consistency stands in stark contrast to the hump-shaped sensitivity pattern seen in mutual fund flows, as documented by Franzoni and Schmalz (2017). This disparity suggests that IVs, compared to mutual funds, exhibit a different investor behavior pattern in response to past performance, particularly in relation to market conditions.

5 Scaling up: capacity of active management with twin IVs

In the subsequent two sections, we underscore the important implications of precise measurement of scale by reevaluating two key metrics in active management. First, we examine the impact of including assets from mutual funds' twin IVs on the estimates of diminishing returns to scale (DRS) at both the fund and industry levels.

Early research on DRS in mutual funds often relied on pooled ordinary least square (OLS) panel regression methods, as seen in studies by Chen et al. (2004); Yan (2008); Ferreira et al. (2013). However, these estimates are unreliable due to the endogeneity issue arising from unobserved managerial skill. This problem of endogeneity could be mitigated by including fund fixed effects in the analysis. However, as explained in Pástor et al. (2015), controlling for fund fixed effects can also introduce finite-sample biases. Pástor et al. (2015) propose a two-stage recursive demean (RD) procedure that avoids finite-sample bias in the fixed effect regressions. Zhu (2018) further shows that the RD procedure of Pástor et al. (2015) suffers an inherent misspecification resulting from a model restriction that is problematic for the fund size process, and Zhu (2018) refines the RD procedure.

In our exercise, we use the fund fixed-effect regression and the approaches of Pástor et al. (2015) and Zhu (2018) to estimate DRS at both the fund level and the industry level. For notational simplicity, we refer to the RD procedure in Pástor et al. (2015) as RD1 and the method of Zhu (2018) as RD2. Unlikely previous work that conducts the analysis at a monthly frequency, our analysis is based on quarterly assets and quarterly returns because institutional assets are only available at a quarterly frequency. To ensure our findings are comparable with prior research, we restrict our analysis to the same sample period as Zhu (2018), which is from 1995 to 2014.

[INSERT TABLE 7 HERE]

Table 7 shows the estimation results. As one can see, by including the twin institutional assets, the fund-level DRS coefficient changes from -0.0723 to -0.0381 based on regression with fund fixed effects, suggesting an overestimation of fund-level DRS by 89.8%. Consistent with Pástor et al. (2015), the fund-level DRS coefficient is negative but not statistically significant under RD1. Still, we find the coefficient changes from -0.403 to -0.0230 once institutional assets are included in the estimation. Based on RD2 of Zhu (2018), the fund-level DRS coefficient also changes from -0.116 to -0.0933. On the other hand, if we represent the scale measure by its logarithm, the fund-level DRS coefficients exhibit minimal change. This is because institutional assets and mutual fund assets under the same strategy are highly correlated (e.g., fund fixed effects and mutual fund assets together explain 86% variation in the IV assets), so taking the logarithm of scale happens to mitigate omitted-variable biases.

Table 7 also shows the results for industry-level DRS estimation. Here, the industry size of mutual funds is calculated as the ratio of mutual fund assets to the aggregate market capitalization, while the total industry size also incorporates the assets of twin IVs. The inclusion of institutional assets under the same investment strategy leads to a notable reduction in the industry-level DRS coefficients, varying between 30% to 50% depending on the specification employed. For instance, under fixed-effect regression, the industry-level DRS coefficient shifts from -0.0197 to -0.0132. This change suggests that prior estimates without institutional assets may have overestimated industry-level DRS by approximately 49.2%. Similarly, using the recursive demeaning approach, the coefficient adjusts from -0.0189 to -0.0130, indicating an overestimation of about 45.4%. It is also worth noting that these findings hold true regardless of whether we analyze gross-fee returns or net-fee returns.

Table 8 conducts similar exercises in Table 7 but is restricted to the subset of mutual funds with twin IVs. We again find that the fund-level and industry-level DRS are significantly smaller once the twin institutional assets are also included. For example, the fund-level DRS coefficient changes from -0.1510 to -0.0791 under RD2, suggesting an overestimation of fund-level DRS by 90.9%. The industry-level DRS coefficients change from around -0.035 to about -0.020 under various estimation methods. Similarly, if one uses the logarithm of the scale measure, the influence of IV assets happens to be neutralized.

[INSERT TABLE 8 HERE]

In summary, neglecting institutional assets under the same investment strategy of mutual funds significantly distorts the estimates of fund-level and industry-level DRS. Our results indicate a greater capacity for active management than previously estimated.[13]

6 Redefining success: dollar value added with twin IVs

Berk and Van Binsbergen (2015) argue that the alpha generated by active funds primarily indicates market rationality and competitiveness, not the skill of the fund managers. They introduce the notion of dollar value added as a more accurate representation of the profit a fund extracts from the markets. This metric is calculated by multiplying a fund's gross excess returns over its benchmark by its assets under management (AUM), and demonstrate evidence of persistence in value added by active equity fund managers.

Clearly, the dollar value added of active fund managers should encompass both the value added from mutual fund vehicles and the value added from institutional investment vehicles. Consequently, the prior estimate, which was based solely on mutual fund assets, is incomplete and necessitates a reexamination of the previous conclusion. We re-examine the effectiveness of active portfolio managers in generating dollar value added, applying the corrected scale measure that includes the assets under management of twin iIVs.

We note that since institutional assets are available at a quarterly frequency, our analysis in this section is also at a quarterly frequency. Every quarter, we calculate the realized value added by taking the AUM from the end of the previous quarter and multiplying it by the returns for that quarter, adjusted according to the Morningstar

[13] It is important to note that this does not necessarily mean that investors would get positive abnormal returns. As argued by Song (2020) and Roussanov et al. (2020), in a market in which investors can not correctly evaluate managerial skill, the deviation of actual fund size from fund capacity would be a key predictor of future performance.

Category Benchmark. These returns are calculated before deducting any fees and are based on the price levels as of the first quarter of 2023.

To set the stage, Table 9 reports the distribution of realized dollar value added, both with and without including assets in the twin IVs, from 1995 to 2023. Based on our sample, the average dollar value added across all fund-quarter observations is \$0.58 million ($t = 1.23$) without institutional assets. This figure increases to \$1.71 million ($t = 2.94$) when considering the total scale measure. Thus, one would significantly underestimate the average dollar value added if a large fraction of AUM under the same investment strategy is left out.

[INSERT TABLE 9 HERE]

We then examine the persistence of dollar value added, closely following the methodology of Berk and Van Binsbergen (2015). Specifically, at the end of each quarter, we compute the average historical value added for each fund by using its quarterly value added over its entire history. We then sort the funds into deciles based on their average historical value added and maintain the composition of each decile for the next h years ($h = 3, ..., 10$). Subsequently, we compute the average value added across funds in each decile and assess whether the top decile outperforms the bottom decile in terms of value added over the next h years. Following this, we generate a time series of dummy variables to indicate whether the top decile outperforms the bottom. Finally, we conduct a binomial test against the null hypothesis, which posits that the probability of the top outperforming the bottom is 50%. The p-values are calculated based on the cumulative distribution function of the binomial distribution.

Table 10 reports the results. Columns (1) and (2) in Panel A show that, when considering only mutual fund assets, the top decile of funds by historical dollar value added continues to add more dollar value than the bottom decile of funds with probabilities of 55.86%, 57.66%, and 54.95% over the next three to five years, respectively. These results allow us to reject the null hypothesis—that there is no difference in dollar value added between the two extreme deciles—at a 90% confidence level for up to five years. However, beyond this time frame, the null hypothesis of no significant difference in value added between the two deciles cannot be rejected.

[**INSERT TABLE 10 HERE**]

Columns (3) and (4) incorporate assets in the twin IVs into the analysis. When measuring value added at the strategy level—by including both mutual fund assets and IV assets—dollar value added exhibits greater persistence. For example, the top decile of funds by historical dollar value added continues to extract more value from the markets than the bottom decile, with probabilities of 59.46%, 61.26%, and 59.46% over the future three to five years, respectively. The corresponding p-values are 1.11%, 0.38%, and 1.12%. Even at an eight-year horizon ($h = 8$), the null hypothesis can be rejected with a 90% confidence level. This indicates that dollar value added becomes more persistent when the scale of a strategy is measured accurately.

These findings align with that active strategies actually have more capacity than previously estimated due to the smaller magnitude of DRS at both the fund level and industry levels. Drawing on the logic of Berk and Van Binsbergen (2015), our results further strengthen the argument that active portfolio managers indeed have the skills to extract rents from the capital markets.

Section 5 and 6 highlight the transformative role of accurately measuring scale through two key metrics in active management. Yet, the implications of our findings on scale measurement surpass these instances. our analysis suggests that the prevalent flow metrics in active management literature are similarly deficient. Additionally, in ongoing work, we find significant influence of incorporating separate accounts in estimating demands of institutional investors. This measurement challenge also affects fixed-income mutual funds and passive investment vehicles, indicating a widespread issue within financial research. For example, Chinco and Sammon (2023), using trading volume, infer that passive ownership is twice the total share of index mutual funds and ETFs in the year of 2021. In Appendix B, we estimate the total assets of passive institutional products. Over our sample period from 1995 to 2023, we find that the average total size of passive institutional products is approximately 80% of the combined assets of passive mutual funds and ETFs.

7 Conclusion

This paper makes one simple point: the scale of active management should be reassessed. By integrating two major datasets on institutional investment products, we identify trillions of dollars in institutional assets that are managed under the same investment strategy as their twin mutual funds, evidenced by a return correlation exceeding 99% (averaging at 99.9%). Because assets in these institutional vehicles adhere to the same investment strategy and thus impact the investment process and strategy-level return performance, we argue that at least 65% more total assets should be included in order to get a complete scale metric for active management.

To illustrate the influence of the twin institutional assets, we revisit the prior work that estimates diminishing returns to scale of mutual funds and that measures whether active fund managers can extract value from the capital markets. When including these twin institutional assets, we find the prior research significantly overestimates diminishing returns to scale at both the fund and industry levels—by up to 90% and 50%, respectively. This suggests that the capacity of active strategies is greater than previously assumed. Additionally, we observe that the dollar value added by active strategies is, on average, higher and more persistent than earlier estimates, reinforcing the notion that active portfolio managers are skilled in extracting rents from the capital markets.

Given that scale is a standard metric in analyzing managerial skill, trading behaviors, and the return performance of mutual funds, the primary insight of this paper has far-reaching implications for the extensive body of mutual fund literature.

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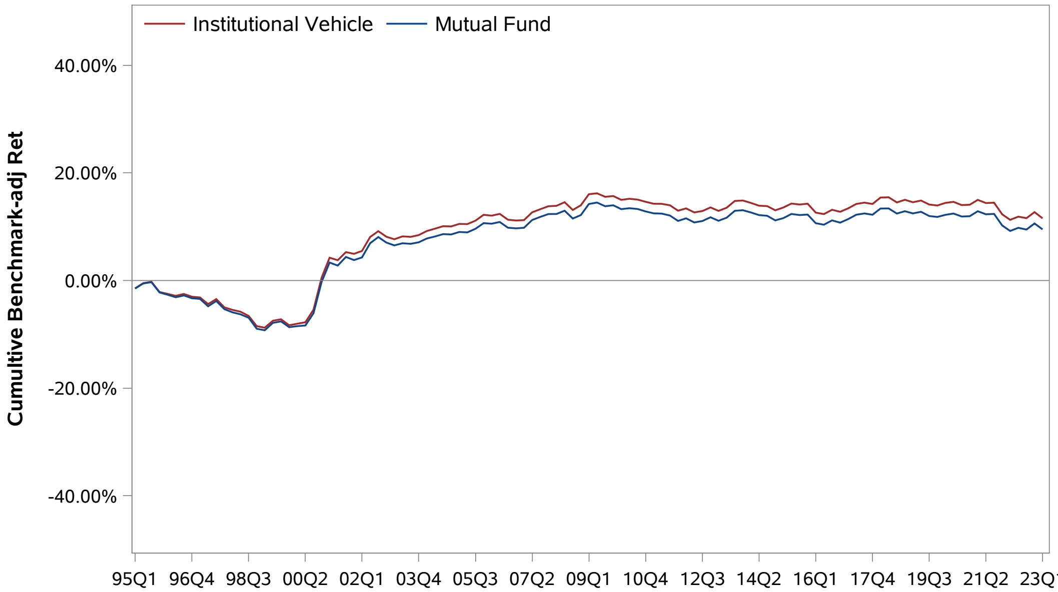
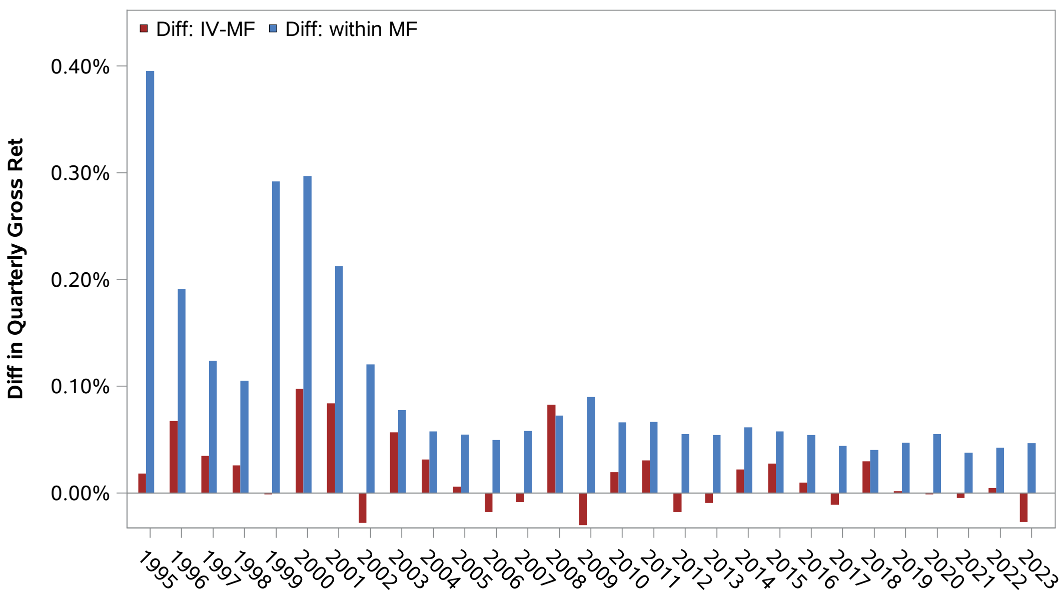
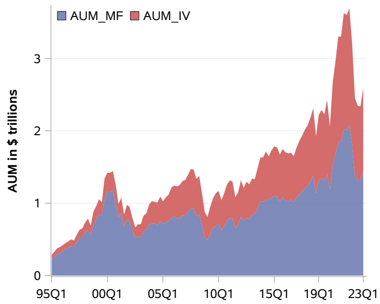


(a) Cumulative returns adjusted by Morningstar category benchmark

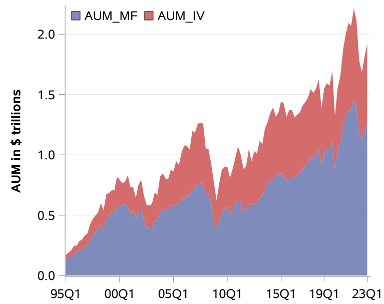


(b) Average difference in quarterly gross returns in each year

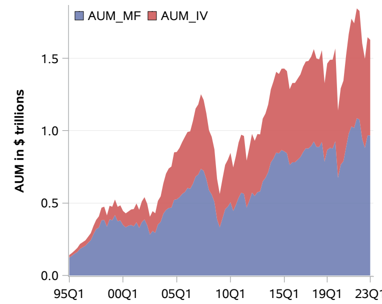
Figure 2: **Difference in gross returns between investment vehicles of the same strategy.** For all mutual fund-IV twins in a given quarter, we form the AUM-weighted portfolios of mutual funds and twin IVs separately. Panel (a) plots the cumulative Morningstar category benchmark-adjusted returns of the mutual fund and the IV portfolios during 1995Q1-2023Q1. Panel (b) plots the average difference in quarterly gross returns between different investment vehicles of the same strategy. We calculate the difference in gross returns between IV and its twin mutual fund (*Diff IV−MF*) each quarter, and we also calculate the range of gross returns across different share classes of the same mutual fund (*Diff within MF*). We plot the AUM-weighted average of *Diff IV−MF* and *Diff within MF* in each year.



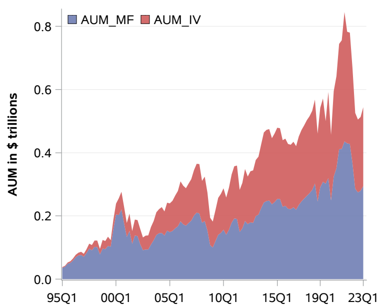
(a) Large-Growth



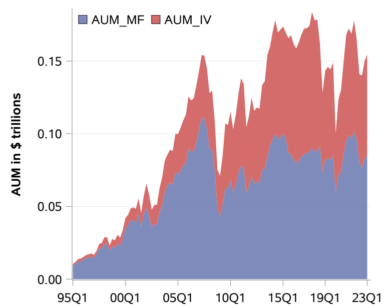
(b) Large-Blend



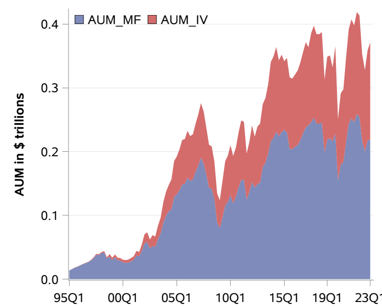
(c) Large-Value



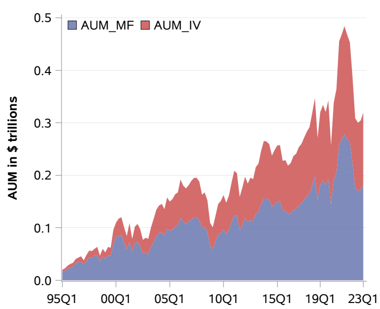
(d) Mid-Growth



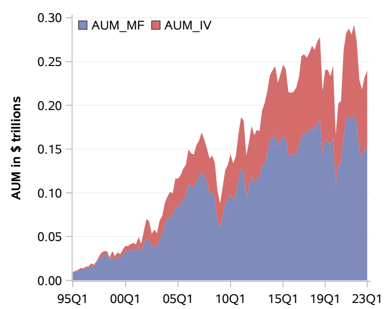
(e) Mid-Blend



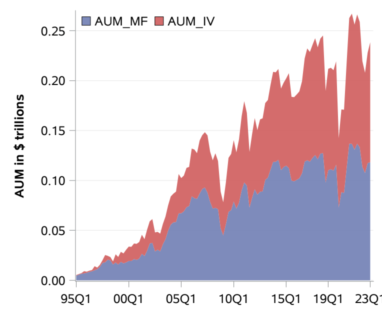
(f) Mid-Value



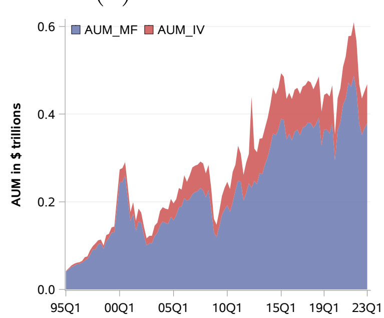
(g) Small-Growth



(h) Small-Blend



(i) Small-Value



(j) Sector

Figure 3: **Summary of active equity mutual funds and twin IVs by categories.** Panels (a) to (j) plot the aggregate AUM of mutual funds and aggregate AUM of the twin IVs by Morningstar categories. Categories in panels (a)-(i) correspond to the 3×3 size-value style box in Morningstar, and category in panel (j) refers to sector equity funds in Morningstar. The sample period is from Q1 1995 to Q1 2023.

Table 1: **Fund characteristics.** This table reports the average value of fund characteristics based on fund-by-quarter observations from 1995.Q1 to 2023.Q1. All AUMs are inflation-adjusted to the price level of 2023.Q1. AUM_MF is the mutual fund AUM. AUM_Total is the sum of the mutual fund AUM and the AUM of the twin IV. Family AUM_MF is the sum of mutual fund AUM across all funds managed by a fund family. Benchmark-adj Gret and Benchmark-adj Nret are the quarterly gross and net returns of mutual funds in excess of the returns of the corresponding Morningstar category benchmark index. Annual MF expense ratio is the AUM-weighted average annual expense ratio across share classes of a mutual fund. MF_Return_Vol is the full-sample monthly mutual fund return volatility. β_{Mkt}, β_{SMB}, β_{HML}, and β_{UMD} are obtained through time-series regression of monthly mutual fund excess returns on Fama and French (1993) and UMD factor for each mutual fund during the whole sample period.

Fund Sample:	without IV	with IV
AUM_MF ($ mi)	1,339	4,429
AUM_Total ($ mi)	1,339	7,295
Family AUM_MF ($ mi)	99,248	97,534
Benchmark-adj Gret(%)	0.01	0.25
Benchmark-adj Nret (%)	−0.34	−0.02
Annual MF expense ratio (%)	1.30	1.11
MF_Return_Vol	0.054	0.052
β_{Mkt}	0.981	0.977
β_{SMB}	0.190	0.248
β_{HML}	0.005	0.042
β_{UMD}	0.004	0.001

Table 2: **Determinants of IV Offering Decisions.** This table analyzes the IV offering decision at mutual fund-by-quarter level observations. For each mutual fund, we identify the quarter when it offers twin IV for the first time. The first-IV-offering quarter is identified based on the availability of IV assets data in either eVestment or Morningstar database. To construct the sample, we retain all fund-by-quarter observations on or before the first-IV-offering quarter. We include mutual funds which never offer IV in our sample period. We generate an indicator variable Dummy_IV_Offer, which equals one for the first-IV-offering quarter for each mutual fund and zero elsewhere. We regress Dummy_IV_Offer in quarter t on a set of fund/style/family-level characteristics measured at the end of quarter $t-1$, including log of mutual fund TNA (Log(MF_TNA)), past four-quarter benchmark adjusted gross returns of the mutual fund (MF_AdjGRet_P4), past four-quarter monthly return volatility of the mutual fund (MF_Vol_P4), past four-quarter average quarterly percentage mutual fund flows (MF_Flow_P4), annual expense ratio of the mutual fund (MF˙Exp˙Ratio), log of mutual fund ages in months (Log(MF_Age)), average past four-quarter returns of mutual funds in the same Morningstar Category (Style_Ret_P4), average past four-quarter quarterly percentage fund flows of mutual funds in the same Morningstar Category (Style_Flow_P4), a dummy variable indicating whether the fund family is among the largest 5% families at the quarter-end (Dummy_Large_Family), a dummy variable indicating whether the fund family already offered an IV before the current quarter (Dummy_Family_IV_Exist), average past four-quarter quarterly percentage fund flows of mutual funds in the same fund family (Family_Flow_P4), and average past four-quarter cumulative returns of mutual funds in the same fund family. Columns (1)-(4) report results from Logit regressions, and columns (5)-(8) report results from OLS regressions. Year-quarter fixed effects are included. Standard errors are clustered by year-quarter.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reg Model:	Logit				OLS			
Log(MF_TNA)	0.2257***			0.1908***	0.0011***			0.0011***
	(5.77)			(4.47)	(4.38)			(3.78)
MF_AdjGRet_P4	1.1489***			0.6391*	0.0068***			0.0041
	(4.51)			(1.80)	(3.25)			(1.47)
MF_Vol_P4	−1.9809			−4.3010**	−0.0081			−0.0251*
	(−1.22)			(−1.99)	(−1.01)			(−1.91)
MF_Flow_P4	0.1370			0.1052	0.0012			0.0015
	(1.47)			(0.89)	(1.47)			(1.13)
MF_Exp_Ratio	−204.2865			−73.0371	−0.5583			0.1053
	(−1.52)			(−0.46)	(−1.24)			(0.13)
Log(MF_Age)	−0.1919**			−0.2507***	−0.0009**			−0.0014**
	(−2.52)			(−2.96)	(−2.20)			(−2.61)
Style_Ret_P4		0.2266		0.3392		0.0006		0.0018
		(0.92)		(1.16)		(0.21)		(0.97)
Style_Flow_P4		2.4384***		−1.6329		0.0356***		−0.0101
		(4.32)		(−1.67)		(2.97)		(−1.65)
Dummy_Large_Family			−0.4427***	−0.0370			−0.0063***	−0.0000
			(−3.86)	(−0.21)			(−4.51)	(−0.03)
Dummy_Family_IV_Exist			1.0970***	0.4356***			0.0124***	0.0024***
			(11.46)	(3.10)			(10.65)	(2.94)
Family_Flow_P4			−0.0007**	-0.0525			−0.0000**	−0.0000***
			(−2.00)	(−0.26)			(−2.21)	(−4.37)
Family_Ret_P4			1.3580***	0.4949			0.0144***	0.0018
			(3.92)	(0.90)			(2.94)	(0.53)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
No. Obs.	131,338	163,865	98,325	86,334	138,813	163,865	98,325	92,747
Pseudo R^2 / Adj. R^2	0.016	0.001	0.021	0.017	0.004	0.003	0.006	0.005

Table 3: **Distribution of gross return correlations.** This table reports the monthly gross return correlation between different investment vehicles of the same investment strategy. The sample period is from January 1995 to March 2023. "Corr - MF&IV" refers to the gross return correlation between mutual fund-IV twins. We also compute pairwise gross return correlations between different share classes within the same mutual fund. "Corr - Share Classes (Avg)" refers to the average of pairwise gross return correlations within the same fund, and "Corr - Share Classes (Min)" refers to the minimum of pairwise gross return correlations within the same fund. "Corr - within Category" refers to the average of pairwise gross return correlations for mutual funds within the same Morningstar category (size-value 3-by-3 categories, plus sector equity category). "Corr - within Family-Category" refers to the average pairwise gross return correlations for mutual funds within the same fund family and the same Morningstar category.

	Mean	SD	P1	P10	P25	P50	P75	P90
Corr - MF&IV	0.999	0.002	0.991	0.996	0.999	1.000	1.000	1.000
Corr - Share Classes (Avg)	0.999	0.013	0.989	1.000	1.000	1.000	1.000	1.000
Corr - Share Classes (Min)	0.998	0.021	0.950	0.999	1.000	1.000	1.000	1.000
Corr - within Category	0.890	0.126	0.429	0.786	0.869	0.922	0.953	0.972
Corr - within Family-Category	0.938	0.069	0.667	0.861	0.924	0.958	0.980	0.995

Table 4: **AUM of mutual funds and identified IVs.** This table reports the sum of AUM across mutual funds and the identified twin IVs at each year end from 1995 to 2022 and at the end of 2023.Q1. The mutual fund sample is based on active US domestic equity funds in Morningstar Direct. Columns (1)-(2) report the number of mutual funds in our sample (# Funds) and their total AUM (AUM_MF) in $ trillions. In columns (3)-(5), we retain the subset of mutual funds with IVs identified from the Morningstar institutional dataset. We report both the total AUM of mutual funds (AUM_MF) and IVs (AUM_IV). In columns (6)-(8), we retain the subset of mutual funds with IVs identified from eVestment. In columns (9)-(11), we retain the subset of funds with IVs identified from either Morningstar or eVestment. If a fund has non-missing IV AUM from both Morningstar and eVestment, we use the institutional AUM from Morningstar. We require IVs to have at least 99% return correlation with their twin mutual funds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fund Sample:	All		with IV from MS			with IV from eV			with IV from MS or eV		
Year	#Funds	AUM_MF ($ tn)	#Funds	AUM_MF	AUM_IV	#Funds	AUM_MF	AUM_IV	#Funds	AUM_MF	AUM_IV
1995	1428	0.83	362	0.27	0.20	458	0.52	0.17	549	0.57	0.21
1996	1577	1.11	391	0.38	0.26	511	0.71	0.22	609	0.78	0.27
1997	1814	1.52	454	0.53	0.40	599	0.98	0.33	704	1.07	0.42
1998	2022	1.90	509	0.69	0.54	662	1.25	0.45	784	1.37	0.57
1999	2210	2.52	547	0.94	0.71	709	1.64	0.58	844	1.80	0.75
2000	2370	2.48	589	0.94	0.73	773	1.61	0.61	922	1.76	0.78
2001	2517	2.19	645	0.87	0.68	847	1.48	0.59	1020	1.60	0.74
2002	2532	1.67	682	0.69	0.57	892	1.18	0.52	1080	1.27	0.63
2003	2553	2.28	725	0.99	0.94	950	1.66	0.86	1154	1.78	1.04
2004	2623	2.63	765	1.18	1.14	1007	1.97	1.09	1222	2.10	1.30
2005	2637	2.84	817	1.33	1.43	1058	2.17	1.34	1296	2.31	1.60
2006	2705	3.19	864	1.53	1.69	1118	2.47	1.58	1371	2.64	1.89
2007	2712	3.34	904	1.63	1.78	1171	2.60	1.66	1433	2.78	2.00
2008	2625	1.92	940	0.97	1.13	1193	1.49	1.03	1470	1.60	1.26
2009	2430	2.48	955	1.27	1.45	1183	1.94	1.25	1465	2.09	1.57
2010	2382	2.82	988	1.46	1.71	1193	2.18	1.44	1488	2.37	1.83
2011	2336	2.64	1039	1.42	1.61	1211	2.06	1.31	1524	2.26	1.70
2012	2313	2.90	1079	1.57	1.78	1214	2.26	1.47	1538	2.49	1.88
2013	2317	3.86	1114	2.09	2.24	1234	3.03	1.83	1569	3.33	2.39
2014	2333	4.13	1138	2.23	2.30	1236	3.22	1.98	1582	3.55	2.51
2015	2309	3.92	1153	2.12	2.33	1236	3.05	1.95	1586	3.36	2.52
2016	2277	4.01	1161	2.19	2.33	1232	3.12	1.97	1586	3.43	2.55
2017	2240	4.57	1147	2.50	2.65	1206	3.57	2.24	1554	3.91	2.91
2018	2200	4.07	1129	2.23	2.32	1199	3.16	1.98	1534	3.45	2.56
2019	2116	4.94	1088	2.75	2.82	1161	3.83	2.43	1480	4.19	3.12
2020	2041	5.63	1058	3.20	3.38	1131	4.35	2.91	1435	4.78	3.74
2021	1976	6.50	1037	3.68	3.80	1117	5.02	3.32	1408	5.51	4.24
2022	1949	4.88	1013	2.70	2.78	1101	3.70	2.50	1383	4.07	3.16
2023(Q1)	1954	5.11	1011	2.83	2.92	1097	3.89	2.68	1379	4.27	3.37

Table 5: **Relation between mutual fund AUM and AUM of twin IVs.** Panel A reports results of the fund-level panel regressions based on all mutual fund-IV twins, and the standard errors are clustered by funds. AUM_MF and AUM_IV are AUM of mutual funds and their twin IVs, respectively. Flow_MF and Flow_IV are the dollar flows of mutual funds and their twin IVs, respectively. Standard errors are clustered by funds. Panel B reports results from quarterly time-series regression. In column (1), the dependent variable is the aggregate AUM of IVs scaled by total stock market value at each quarter end. The independent variable is the aggregate AUM of mutual funds scaled by total stock market value. In column (2), the dependent variable is the aggregate dollar flows of IVs scaled by total stock market value at each quarter end. The independent variable is the aggregate dollar flows of mutual funds scaled by total stock market value at each quarter end. *t*-statistics are computed with Newey-West correction of 4 lags.

Panel A: Fund-level AUM and Flow

DepVar:	(1) AUM_IV	(2) AUM_IV	(3) Flow_IV	(4) Flow_IV
AUM_MF	0.6720***	0.6629***		
	(4.37)	(4.64)		
Flow_MF			0.5294***	0.5704***
			(3.73)	(4.10)
Fund FE	N	Y	N	Y
No. Obs.	87,841	87,832	87,841	87,832
R^2	0.5487	0.8602	0.0065	0.0111

Panel B: Industry-level AUM and Flow

DepVar:	(1) IndustrySize_IV	(2) IndustryFlow_IV
IndustrySize_MF	1.042***	
	(4.67)	
IndustryFlow_MF		0.9332***
		(5.95)
No. Obs.	113	113
R^2	0.4870	0.1576

Table 6: **Flow-to-performance sensitivity of mutual funds and IVs.** This table shows the flow-to-performance sensitivity of MFs and IVs separately. The sample period is 1995Q1-2023Q1. We regress the percentage fund flows of MFs or IVs in quarter t on fund gross returns (Panel A) or fund benchmark adjusted gross returns (Panel B) in quarter $t-1$. We control for the TNA of MF or IV at the end of quarter $t-1$ and include fund fixed effects and year-quarter fixed effects. In columns (3)-(4) and (7)-(8), we add the interaction term between fund performance and Moderate, which is a dummy variable that equals one if CRSP value-weighted market return is between -5% and $+5\%$ in quarter $t-1$ and zero elsewhere. Standard errors are clustered by Morningstar Category×Time.

Panel A: Gross Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	MFs				IVs			
GRet	0.492***	0.477***	0.407***	0.393***	0.326***	0.307***	0.291***	0.279***
	(15.56)	(15.21)	(10.49)	(10.13)	(5.15)	(4.96)	(3.72)	(3.63)
GRet×Moderate			0.330***	0.321***			0.134	0.110
			(5.23)	(5.14)			(1.07)	(0.88)
TNA	−0.000***	0.000	−0.000***	0.000	−0.000***	−0.000***	−0.000***	−0.000***
	(−12.73)	(0.25)	(−12.85)	(0.29)	(−10.22)	(−7.88)	(−10.23)	(−7.89)
Fund FE	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
No. Obs.	75,598	75,574	75,598	75,574	75,598	75,574	75,598	75,574
Adj. R^2	0.0266	0.0632	0.0272	0.0638	0.00432	0.0347	0.00432	0.0347

Panel B: Benchmark-Adjusted Gross Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	MFs				IVs			
AdjGRet	0.682***	0.649***	0.589***	0.561***	0.508***	0.473***	0.467***	0.421***
	(16.50)	(16.14)	(11.58)	(11.27)	(6.53)	(6.21)	(4.96)	(4.59)
AdjGRet×Moderate			0.335***	0.318***			0.147	0.187
			(4.12)	(4.01)			(0.89)	(1.13)
TNA	−0.000***	0.000	−0.000***	0.000	−0.000***	−0.000***	−0.000***	−0.000***
	(−12.30)	(0.73)	(−12.32)	(0.72)	(−10.06)	(−7.84)	(−10.06)	(−7.84)
Fund FE	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
No. Obs.	75,566	75,542	75,566	75,542	75,566	75,542	75,566	75,542
Adj. R^2	0.0270	0.0633	0.0273	0.0636	0.00448	0.0349	0.00448	0.0349

Table 7: **Relation between scale and subsequent performance.** This table shows the estimation results of DRS at the fund level and industry level. The unit of observations is at the fund-by-quarter level, and the sample period is 1995.Q1-2023.Q1. The dependent variable is the average monthly gross or net fund returns in excess of the Morningstar category benchmark index within each quarter. In FE regressions, we control for fund fixed effects, and the standard errors are clustered by Morningstar category × quarter. RD1 and RD2 stand for recursive demeaning regression methods of Pástor et al. (2015) and Zhu (2018), respectively. Standard errors in RD are clustered by funds. We also report R-square from the first-stage regression of RD. In Panel A, fund size is measured by mutual fund dollar assets, and industry size is measured by the sum of mutual fund assets scaled by total stock market value. In Panel B, fund size is measured by the sum of mutual fund assets and the twin IV assets, and industry size is measured by the total mutual fund assets and IV assets scaled by total stock market value. In Panel C and Panel D, we take the natural logarithm on the scale measures.

Panel A: Dollar AUM_MF										
DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
FundSize_MF (Coef.×10^6)		−0.0723***		−0.4029	−0.1155***		−0.0715***		−0.4075	−0.1139***
		(−9.40)		(−0.59)	(−2.77)		(−9.33)		(−0.60)	(−2.77)
IndustrySize_MF	−0.0197**	−0.0182*	−0.0189***	−0.0176***	−0.0175***	−0.0187*	−0.0172*	−0.0179***	−0.0166***	−0.0165***
	(−2.06)	(−1.91)	(−6.53)	(−5.91)	(−5.91)	(−1.96)	(−1.81)	(−6.23)	(−5.60)	(−5.60)
First-stage R^2				0.00	0.09				0.00	0.09
Panel B: Dollar AUM_Total										
DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
FundSize_Total (Coef.×10^6)		−0.0381***		−0.0230	−0.0933**		−0.0376***		−0.0248	−0.0905**
		(−8.99)		(−0.83)	(−2.08)		(−8.92)		(−0.88)	(−2.07)
IndustrySize_Total	-0.0132***	-0.0125***	-0.0130***	-0.0126***	-0.0121***	-0.0127***	-0.0120***	-0.0125***	-0.0121***	-0.0117***
	(−3.24)	(−3.08)	(−13.30)	(−12.77)	(−12.15)	(−3.11)	(−2.95)	(−12.81)	(−12.29)	(−11.70)
First-stage R^2				0.01	0.05				0.01	0.05
Panel C: Ln(AUM_MF)										
DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
Ln(FundSize_MF)		−0.0018***		−0.0071***	−0.0024***		−0.0017***		−0.0066***	−0.0023***
		(−15.50)		(−4.90)	(−18.41)		(−15.23)		(−4.57)	(−18.85)
IndustrySize_MF	−0.0197**	−0.0031	−0.0189***	−0.0165***	−0.0121***	−0.0187*	−0.0024	−0.0179***	−0.0156***	−0.0112***
	(−2.06)	(−0.33)	(−6.53)	(−5.64)	(−4.13)	(−1.96)	(−0.26)	(−6.23)	(−5.34)	(−3.85)
First-stage R^2				0.00	0.12				0.00	0.12
Panel D: Ln(AUM_Total)										
DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
Ln(FundSize_Total)		−0.0016***		−0.0080***	−0.0022***		−0.0016***		−0.0074***	−0.0022***
		(−15.60)		(−4.09)	(−16.72)		(−15.34)		(−3.78)	(−17.22)
IndustrySize_Total	−0.0132***	−0.0055	−0.0130***	−0.0120***	−0.0092***	−0.0127***	−0.0051	−0.0125***	−0.0115***	−0.0088***
	(−3.24)	(−1.38)	(−13.30)	(−12.35)	(−9.59)	(−3.11)	(−1.29)	(−12.81)	(−11.87)	(−9.17)
First-stage R^2				0.00	0.10				0.00	0.10

Table 8: **Relation between scale and fund performance: Within Fund-quarters with institutional AUM.** In this table, we retain the fund-by-quarter observations with AUM available from IVs. Then, we re-perform the regression analyses as in Table 7.

Panel A: Dollar AUM_MF

DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
FundSize_MF (Coef.$\times 10^6$)		−0.0474***		0.0381	−0.1510**		−0.0468***		0.0304	−0.1461**
		(−6.55)		(0.55)	(−2.16)		(−6.49)		(0.42)	(−2.15)
IndustrySize	−0.0356***	−0.0308**	−0.0350***	−0.0354***	−0.0343***	−0.0345***	−0.0297**	−0.0339***	−0.0340***	−0.0329***
	(−2.94)	(−2.53)	(−5.95)	(−5.77)	(−5.63)	(−2.85)	(−2.44)	(−5.76)	(−5.56)	(−5.42)
First-stage R^2				0.00	0.04				0.00	0.04

Panel B: Dollar AUM_Total

DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
FundSize_Total (Coef.$\times 10^6$)		−0.0248***		−0.0119	−0.0791*		−0.0244***		−0.0141	−0.0761*
		(−6.68)		(−0.55)	(−1.88)		(−6.61)		(−0.62)	(−1.86)
IndustrySize_Total	−0.0207***	−0.0190***	−0.0206***	−0.0205***	−0.0199***	−0.0201***	−0.0185***	−0.0200***	−0.0199***	−0.0192***
	(−4.39)	(−4.05)	(−10.39)	(−10.13)	(−9.76)	(−4.25)	(−3.92)	(−10.10)	(−9.85)	(−9.50)
First-stage R^2				0.03	0.04				0.03	0.04

Panel C: Ln(AUM_MF)

DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
Log(FundSize_MF)		−0.0016***		−0.0023***	−0.0018***		−0.0016***		−0.0021***	−0.0017***
		(−14.65)		(−3.98)	(−13.02)		(−14.39)		(−3.65)	(−12.72)
IndustrySize_MF	−0.0356***	0.0000	−0.0350***	−0.0348***	−0.0282***	−0.0345***	0.0004	−0.0339***	−0.0334***	−0.0270***
	(−2.94)	(0.00)	(−5.95)	(−5.75)	(−4.70)	(−2.85)	(0.03)	(−5.76)	(−5.54)	(−4.51)
First-stage R^2				0.01	0.15				0.01	0.15

Panel D: Ln(AUM_Total)

DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE			RD1	RD2	FE			RD1	RD2
Log(FundSize_Total)		−0.0016***		−0.0018***	−0.0017***		−0.0016***		−0.0016**	−0.0017***
		(−15.64)		(−2.69)	(−11.60)		(−15.52)		(−2.44)	(−11.44)
IndustrySize_Total	−0.0207***	−0.0088*	−0.0206***	−0.0200***	−0.0177***	−0.0201***	−0.0084*	−0.0200***	−0.0193***	−0.0171***
	(−4.39)	(−1.87)	(−10.39)	(−10.06)	(−9.05)	(−4.25)	(−1.78)	(−10.10)	(−9.79)	(−8.78)
First-stage R^2				0.01	0.15				0.01	0.15

Table 9: **Cross-sectional distribution of dollar value added.** We estimate the average quarterly dollar value added during 1995.Q1-2023.Q1. We use two metric measures: AUM_MF is the mutual fund assets, and AUM_Total includes both mutual fund assets and assets in twin IVs. We report the cross-sectional mean, t-statistic, and percentile values based on the distribution of value added in the cross-section of funds. The cross-sectional weighted mean and t-statistic are computed by weighting the number of periods the fund exists in the sample period. Percent with negative value added is the fraction of the distribution that has negative value added. The numbers are reported in 2023Q1 dollar per quarter (in millions).

AUM measure:	AUM_MF	AUM_Total
Cross-sectional weighted mean	0.58	1.71
t-statistic	1.23	2.94
Cross-sectional mean	−0.79	−0.65
t-statistic	−2.09	−1.28
Percentile values:		
p1	−55.87	−84.99
p5	−17.06	−25.01
p10	−7.43	−10.95
p50	−0.23	−0.27
p90	5.32	9.10
p95	12.84	23.42
p99	54.60	87.41
Percent Value-added<0	0.61	0.60

Table 10: **Persistence of dollar value added.** This table analyzes the persistence of dollar value added. The analysis is based on quarterly value added during 1995.Q1-2023.Q1. We use two AUM measures for value added: AUM_MF is mutual fund assets, and AUM_Total includes both mutual fund assets and assets in twin IVs. At each quarter end, we compute the average value added for each fund using all its history. We sort the funds into deciles by their historical average value added and hold the funds in each decile over the next h years ($h = 3, ..., 10$). In each quarter, we compute the equal-weighted average value added across funds in a given decile over the h-year period and examine whether the top decile outperforms the bottom decile. We repeat this procedure over all quarters and obtain time series of dummy variables indicating whether the top outperforms the bottom decile. Finally, we perform a binomial test on the null hypothesis: the probability of the top outperforming the bottom decile is 50% in each quarter. p-values are calculated based on the cumulative distribution function of the binomial distribution. We also report the fraction of quarters when the top outperforms the bottom decile.

AUM Measure:	AUM_MF		AUM_Total	
Horizon (Years)	Freq (%)	p-value (%)	Freq (%)	p-value (%)
3	55.86	6.42	59.46	1.11
4	57.66	2.86	61.26	0.38
5	54.95	9.18	59.47	1.12
6	54.05	12.73	58.56	1.82
7	52.25	22.39	57.66	2.86
8	48.65	50.00	54.95	9.18
9	48.65	50.00	53.15	17.13
10	48.65	50.00	54.05	12.73

Appendix

A Matching Morningstar with eVestment

In this section, we describe the procedure to match mutual fund share classes in Morningstar with their twin IVs in eVestment.

We use the Traditional Consultant dataset from eVestment. The Traditional Consultant dataset is a survivorship bias-free dataset that provides information about investment strategies at firm level, product level, and vehicle level. Specifically, a "product" in eVestment refers to a strategy, and a "vehicle" in eVestment is an investment vehicle under a product/strategy (comparable to a share class of mutual fund). For each vehicle, eVestment reports its vehicle name and its security identifier (i.e., CUSIP, Ticker, ISIN), if available. Thus, we mainly utilize the name and security identifier of eVestment vehicles to match with mutual fund share classes in Morningstar. Once an eVestment vehicle is matched with a mutual fund share class in Morningstar, we can match the parent product of the eVestment vehicle to the parent mutual fund of the share class in Morningstar. Under this matching method, an eVestment product can only be matched with a Morningstar mutual fund if at least one mutual fund vehicle is reported under that product in eVestment.

We start with the "ProductVehicles" file in eVestment, which provides identifying information of the vehicles. We retain US vehicles that are marked as "Fund (Pooled/Mutual)," since only these vehicles can be potentially matched with mutual fund share classes in Morningstar. Next, we use the security identifier (CUSIP, Ticker, or ISIN, depending on the data availability) to match with share classes in Morningstar. During this procedure, once an eVestment vehicle is successfully matched with a mutual fund share class in Morningstar, we define the parent product of the eVestment vehicle is matched with the parent mutual fund of the share class in Morningstar. After that, we are left with eVestment vehicles that either do not have a security identifier or fail to be matched through the security identifier. We then use the vehicle name and other information to find matches for the remaining eVestment vehicles. In the name-matching procedure, we utilize the vehicle name, the product name, and the asset management company name to manually pair eVestment vehicles with Morningstar share classes. In this procedure, we also cross-check with fund names in CRSP Mutual Fund database if an eVestment vehicle has a Ticker or a CUSIP.

After the above matching procedure, we obtain 2,167 pairs of matched eVestment product-Morningstar mutual fund. The majority of these pairs are one-to-one match between eVestment products and Morningstar mutual funds, but there also exist two types of "duplicated matches": (*i*) a Morningstar mutual fund could be matched with more than one eVestment products (involving 295 mutual funds), and (*ii*) an eVestment product could be matched with more than one Morningstar mutual fund (involving 57 eVestment prodcuts). For the first type of duplicated matches, for a focal mutual fund, we retain the product that is most likely to be linked with the mutual fund. This is achieved by manually comparing the product name with the mutual fund name and comparing the product returns with the mutual fund returns. For the second type of duplicated matches, for a focal product, we retain the mutual fund with the largest AUM. After correcting these duplicated matches, we end up with 1,837 pairs of eVestment product-Morningstar mutual fund that are one-to-one matched.

B Remeasuring Passive AUM

In this section, we identify and measure the total scale of passively managed institutional products. We show that trillions of assets are allocated to passive institutional products beyond assets managed by passive mutual funds or ETFs. Below, we begin by describing the procedure of identifying passive institutional vehicles (IVs), and then we show summary statistics on the assets managed by passive funds (mutual funds and ETFs) and IVs.

We identify passive IVs from two sources: (*i*) Following the matching procedure for active mutual funds and their twin IVs in the main draft, we match passive mutual funds with their twin IVs in eVestment or Morningstar;[14] (*ii*) For the IVs without twin mutual funds offering, we restrict to institutional products in Morningstar and conduct a comprehensive identification procedure to identify passively managed IVs.[15]

The procedure for identifying passive IVs goes as follows. In the first step, among the IVs in Morningstar, we identify those with names containing "Index" or "Idx" as passive IVs. In the second step, we focus on the subset of IVs that report a primary benchmark index in their prospectus, and we calculate the monthly (gross) return correlation between each separate account and its prospectus benchmark index. We identify those with return correlations greater than 0.98 as passively managed.

In the third step, among the rest of the IVs not identified as passive in Step one and Step two, we retain IVs whose name contains keywords that imply they are in-

[14] We define a mutual fund as a passive fund if it is flagged as an index fund in Morningstar or its name contains "Index."

[15] Here, we cannot simultaneously include IVs without twin mutual funds from eVestment and from Morningstar, since there is not a common identifier to link eVestment IVs to Morningstar IVs. Thus, including IVs from both databases would cause a double-counting problem. To be consistent with our main draft, here we choose to use Morningstar as the data source for identifying passive IVs without twin mutual funds.

dex trackers.[16] Specifically, we retain IVs whose names contain one of the following keywords: "S&P", "RUSS", "RUSSELL", "R1000", "R2000", "R3000", "MSCI", "NASDAQ", "VANGUARD" (for Vanguard vehicles tracking CRSP indexes). Next, we manually examine these IVs, and we take two criteria for identifying passive IVs: (1) we can clearly identify an index name from the name of the IV (e.g., "AIA S&P 1500 AllCap"); (2) we search for the information about the strategy of the IV through its official website or professional third-party website and judge whether the strategy is passive. Finally, we exclude those IVs with twin mutual funds to avoid double counting the passive IVs that are already identified in the source (*i*).

After identifying passive IVs, we set out to investigate their assets under management. We define institutional assets similar to that in our main draft. For IVs with twin mutual funds, if data on the institutional assets from both eVestment and Morningstar are available, we use the institutional assets from Morningstar. For IVs without twin mutual funds, we use the total assets reported in Morningstar.

Figure B.1 shows the total assets of passively managed mutual funds, ETFs, and passive IVs. One can see a tremendous growth of passive investments, especially in the latter half of our sample period. The total assets of the passive vehicles have grown from \$0.17 trillion to \$11.13 trillion during 1995-2023. Moreover, a significant portion of passive assets are allocated to IVs. When our sample starts in 1995, the total assets of passive funds (including mutual funds and ETFs) are \$50 billion, and the total assets of passive IVs are \$120 billion. By the end of our sample period in 2023Q1, the total assets of passive funds have grown to \$7.59 trillion, and the total assets of passive IVs have grown to \$3.54 trillion, which is about 47% of passive fund assets. In an average

[16] Here, we consider indexes from the top five index providers in the US market: S&P Dow Jones, FTSE Russell, CRSP, MSCI, and Nasdaq (An et al., 2023).

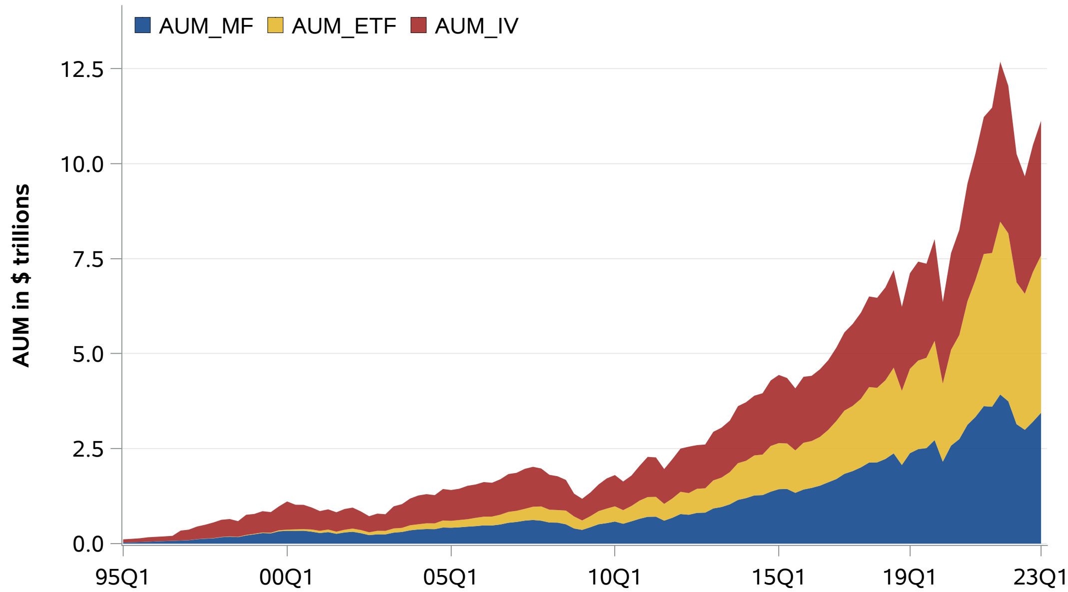


Figure B.1: **AUM of passive mutual funds, ETFs, and institutional vehicles.** This figure shows the AUM (in \$ trillions) of passive equity mutual funds, equity ETFs, and passive equity separate accounts in each quarter.

year, passive institutional products are about 80% the total size of index mutual funds and ETFs. Table B.1 reports detailed statistics at each year-end.[17]

[17] In Table B.1, we only count mutual funds or ETFs with total assets reported in Morningstar Direct. That's why the number of ETFs in the year 1995 is zero in this table.

Table B.1: **AUM of passive mutual funds, ETFs, and passive IVs.** This table reports the sum of AUM across mutual funds, ETFs and the passive IVs at each year end from 1995 to 2022 and at the end of 2023.Q1. The passive mutual fund sample is based on passive US domestic equity funds in Morningstar Direct. The ETF sample is based on US domestic ETFs in Morningstar Direct. The passive IVs are identified in the procedure described in Appendix Section B. A fund or an IV is counted in the statistics only when its total assets are reported in Morningstar Direct. Columns (2)-(3) report the number of passive mutual funds (# Passive MFs) and ETFs (# ETFs) in our sample. Column (4) reports the AUM of passive mutual funds and ETFs in $ trillions. Column (5) reports the AUM of passive IVs in $ trillions.

(1) Year	(2) # Passive MFs	(3) # ETFs	(4) AUM_Funds ($tn)	(5) AUM_IVs
1995	67	0	0.05	0.12
1996	80	1	0.08	0.26
1997	96	1	0.15	0.41
1998	118	2	0.23	0.53
1999	151	3	0.35	0.63
2000	185	40	0.37	0.58
2001	202	58	0.37	0.55
2002	222	71	0.34	0.45
2003	231	77	0.48	0.70
2004	246	109	0.61	0.83
2005	235	151	0.68	0.88
2006	225	278	0.84	1.00
2007	245	384	0.98	1.00
2008	234	392	0.72	0.60
2009	208	406	0.92	0.79
2010	214	447	1.13	0.92
2011	224	523	1.19	1.03
2012	225	509	1.46	1.15
2013	228	529	2.12	1.50
2014	231	558	2.57	1.72
2015	242	634	2.65	1.74
2016	242	718	3.23	1.93
2017	263	779	4.12	2.38
2018	267	844	4.02	2.21
2019	269	894	5.34	2.68
2020	262	971	6.38	3.10
2021	264	1140	8.47	4.21
2022	263	1232	7.15	3.34
2023 (Q1)	268	1251	7.59	3.54

C Additional Results

In this section, we present some supporting and additional results. In Table C.1, we evaluate performance of the aggregate portfolio of mutual funds with and without twin IV offered using factor models. The aggregate portfolio of mutual funds without IV twins significantly underperfom the aggregate portfolio of mutual funds with twin IVs both before and after fees.

Table C.1: **Performance of aggregate active fund portfolio.** This table shows the time-series regressions of monthly excess returns of aggregate active fund portfolio on Fama and French (1993) three factors and momentum factor during 1995.01-2023.03. To measure the portfolio returns, we consider gross returns (ExGRet) in Panel A and net returns in Panel B (ExNRet). In both panels, we construct the aggregate active fund portfolio in four ways: (1) We use all active US equity mutual funds and use their lagged mutual fund AUM as portfolio weights (ExGret1/ExNRet1); (2) We use all active US equity mutual funds and use their lagged mutual fund plus twin IV AUM as portfolio weights (ExGret2/ExNRet2); (3) We use active US equity mutual funds without IVs and use their lagged mutual fund AUM as portfolio weights (ExGret3/ExNRet3); (4) We use active US equity mutual funds with IVs and use their lagged mutual fund plus twin IV AUM as portfolio weights (ExGret4/ExNRet4). Alphas (annualized) in this table refer to the intercepts (multiplied by 12) from the time-series regressions. t-statistics in parentheses are with Newey-West correction of 12 lags.

Panel A: Gross ret								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DepVar:	ExGRet1	ExGRet2	ExGret3	ExGret4	ExGRet1	ExGRet2	ExGret3	ExGret4
Alpha	−0.360	−0.192	−1.128*	0.000	−0.396	−0.204	−1.236**	0.000
	(−0.91)	(−0.50)	(−1.67)	(0.02)	(−1.05)	(−0.59)	(−2.03)	(0.01)
MKTRF	1.001***	0.996***	0.992***	0.994***	0.989***	0.985***	0.980***	0.984***
	(94.25)	(106.23)	(51.48)	(102.94)	(89.94)	(106.50)	(52.85)	(119.65)
SMB					0.084***	0.073***	0.117***	0.062***
					(8.88)	(6.80)	(6.81)	(4.56)
HML					−0.020*	−0.007	−0.059**	0.005
					(−1.73)	(−0.58)	(−2.58)	(0.37)
UMD					0.009	0.003	0.031*	−0.002
					(0.84)	(0.37)	(1.91)	(−0.20)
No. Obs.	339	339	339	339	339	339	339	339
Adj. R2.	0.985	0.987	0.964	0.988	0.989	0.990	0.974	0.990
Panel B: Net Ret								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DepVar:	ExNRet1	ExNRet2	ExNRet3	ExNRet4	ExNRet1	ExNRet2	ExNRet3	ExNRet4
Alpha	−1.26***	−1.104***	−2.064***	−0.888**	−1.284***	−1.116***	−2.16***	−0.888***
	(−3.16)	(−2.99)	(−3.10)	(−2.46)	(−3.43)	(−3.29)	(−3.56)	(−2.75)
MKTRF	1.001***	0.997***	0.992***	0.994***	0.989***	0.986***	0.980***	0.984***
	(94.48)	(106.18)	(52.95)	(102.91)	(89.49)	(105.77)	(53.30)	(119.17)
SMB					0.083***	0.073***	0.114***	0.061***
					(8.73)	(6.60)	(7.03)	(4.47)
HML					−0.019*	−0.007	−0.055**	0.005
					(−1.70)	(−0.57)	(−2.47)	(0.36)
UMD					0.008	0.003	0.029*	−0.002
					(0.80)	(0.33)	(1.80)	(−0.21)
No. Obs.	339	339	339	339	339	339	339	339
Adj. R2.	0.985	0.988	0.966	0.988	0.989	0.990	0.975	0.990