Remeasuring Scale in Active Management*

October 2023

Abstract

We argue at least 65% more total assets should be included in estimating the relationship between scale, managerial skill, and return performance of active equity mutual funds. By combining 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 return correlation higher than 99%. When including these institutional assets in the scale metric, we find prior research overestimates fund-level and industry-level diminishing returns to scale of mutual funds by up to 90% and up to 50%, respectively. We also find that dollar value added of active strategy is higher and more persistent than previously estimated.

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 settings examining mutual fund performance, managerial skill, and trading behaviors, as seen in studies by, for example, Pollet and Wilson (2008); Berk and Van Binsbergen (2015); Pástor et al. (2020); Song (2020); Roussanov et al. (2020); Kaniel et al. (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 active equity mutual funds. Specifically, by combining two major datasets on institutional investment products, we find that, in an average year, more than half of active equity mutual funds have "twin" institutional vehicles (IVs) offered to institutional investors.[1] These IVs are managed under the same investment strategy as their twin mutual funds, with return correlation higher than 99%.[2] When our sample starts in 1995, the twin IVs managed 25% as much as the total active equity mutual fund assets. This proportion

[1]Institutional vehicles are often in the form of separately managed accounts (SMAs), collective investment trusts (CITs), or commingled funds (CFs). Note that SMAs, CITs, or 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 correlation to be 95% for twin status.

escalated to about 66% in 2008 and has remained stable since. When our sample ends in 2023, the assets in the twin IVs mount to $3.37 trillion, which is 65.8% of the total active equity mutual fund assets.

It is clear that assets in these twin IVs also influence security choice and asset allocation, generate price impact, and incur transaction costs, all of which ultimately affect strategy-level performance and thus the performance of mutual fund—one of the various vehicles of the same investment strategy. As a result, these trillions of institutional assets should be included in the scale metric if one studies the relationship between scale and managerial skill, trading activities, or return performance of active management.[3]

To demonstrate the importance of accurately measuring the scale of active management, we undertake two case studies: (*i*) diminishing returns to scale of mutual funds (e.g., Pástor et al., 2015) and (*ii*) dollar value added of mutual funds (Berk and Van Binsbergen, 2015). When including assets in twin IVs into the scale metric, we find the negative relationship between scale and subsequent return performance is overestimated by as much as 90% at the mutual fund level and up to 50% at the industry level, thereby underestimating the actual capacity for active management. When twin IV assets are accounted for, we find active portfolio managers can add more value in total, and the dollar value added becomes more persistent, strengthening the argument that portfolio managers possess

[3]It is acknowledged that IVs and mutual funds exhibit various differences, encompassing aspects like managerial fiduciary duty, sensitivity of flows, and the level of shareholder activism. Our focus is the influence of the twin IV assets on mutual fund trading and return performance since these IVs adhere to the same investment strategy as their twin mutual funds.

skills to extract rents from the financial markets.

While we only conduct two case studies, the message of this paper has much broader implications: our findings indicate that the flow metric used in some prior studies is likely to be incomplete. Likewise, the flow and scale metrics of fixed-income mutual funds are subject to the same measurement issue, as well as those of passively managed investment vehicles. For example, Chinco and Sammon (2023), based on trading volume, infer that passive ownership is twice as large as the total share of index mutual funds and ETFs in the year of 2021. In Appendix B, we show that a large proportion of the "missing" passive shares are held in passive institutional products.[4]

This paper is organized in two parts. In the first part, we explain in detail our data sources, particularly how we link mutual funds to their twin IVs. In particular, we gather our data on IVs from Morningstar and eVestment, two 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. Specifically, Morningstar assigns a strategy identifier (Morningstar Strategy ID) that connects mutual fund share classes and IVs that follow the same investment strategy. eVestment links separately managed accounts, collective investment trusts, or commingled funds with the mutual fund version of the same investment product. This

[4]For example, over our sample period from 1995 to 2023, passive institutional products, on average, manage 80% total assets as the total assets of passive mutual funds and ETFs.

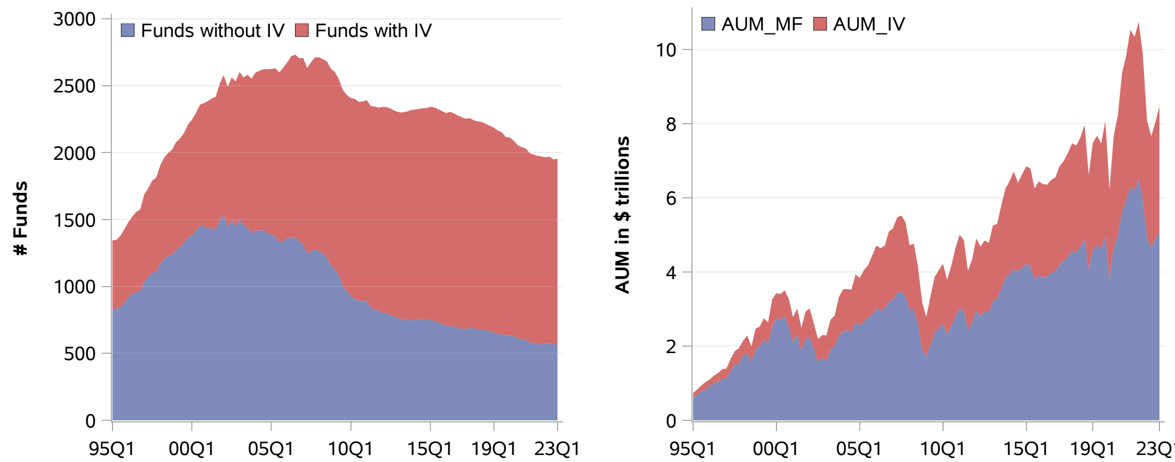
[5]Another notable data source is Informa Investment Solutions (IIS), which is used by Busse et al. (2010). Gerakos et al. (2021) obtain data from a global consulting firm without name disclosed.

allows us to connect mutual funds with their twin IVs.

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 managers using the same strategy (Del Guercio and Tkac, 2002; Busse et al., 2010). To be conservative in capturing "identical" IV-mutual fund twins, *we require the IVs to have at least 99% return correlation with their twin mutual funds.* Due to this strict requirement, the average return correlation between mutual fund-IV twin is similar to the average pairwise return correlation between share classes of the same mutual fund (0.999 vs. 0.999). Moreover, the average difference in gross returns between mutual fund-IV twin is actually smaller than the average range of gross return differences among share classes of the same mutual fund. Researchers often combine assets in different share classes of the same mutual fund as they follow 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 shows the number and total assets of actively managed equity mutual funds in Morningstar Direct,[6] as well as the subset of mutual funds for which twin IVs are identified based on either the Morningstar database or eVestment database. When our sample starts in 1995, 549 out of 1428 active equity mutual funds in Morningstar Direct have IVs identified based on the 99% return correlation standard. These IVs manage in

[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.

total $210 billion of assets, which is 25% of the total assets managed by active equity mutual funds. When our sample ends in 2023, 1379 out of the 1954 active equity mutual funds have twin IVs identified. These twin IVs in total manage $3.37 trillion of assets, which is 65.8% of the total assets managed by active equity mutual funds. In an average year during 1995 to 2023, about 56% of mutual funds have twin IVs identified under the 99% return correlation requirement. We note that our estimation of "twin" IV assets is likely to be a lower bound due to this restrictive threshold.

Besides their sheer size, we also find that assets in these IVs and assets in their twin mutual funds are highly correlated. Thus, it is essential to include these institutional assets in order to get an unbiased estimate of the influence of scale on managerial skill, trading behaviors, and return performance of active mutual funds.

In the second part of the paper, we conduct two case studies to illustrate the importance of accurately measuring scale in active management. In the first case, we revisit the analysis of diminishing returns to scale (DRS) of active equity mutual funds. In particular, we use the fixed-effect regression and the recursive demean approach of Pástor et al. (2015) and Zhu (2018) to estimate both fund-level and industry-level DRS.[7] As institutional assets are highly correlated with mutual fund assets, we find that if one uses the dollar AUM of mutual funds in the regression analysis, the fund-level DRS could be overestimated by up to 90%. On the other hand, when fund size is represented by its logarithm, the magnitude of fund-level DRS happens to be much less affected. In addition, 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 the industry-level DRS is over-estimated by as much as 50%. These findings indicate that active asset management actually has a higher capacity than previous estimates.

The performance at the strategy level is shaped by assets from both mutual funds and twin IVs. The dollar value added, as estimated in Berk and Van Binsbergen (2015) using only mutual fund assets, might not capture the complete picture. In our second case study, we re-calculate the dollar value added at the strategy level. We estimate that the average dollar value added over fund-quarter observations is \$0.58 million without institutional assets and \$1.71 million adding the assets in twin IVs of mutual funds. In other words, the

[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 by active portfolio managers is significantly underestimated without the twin IV assets. In addition, we find that dollar value added is more persistent than what the prior study suggested. This is expected as the capacity of active management is actually higher.

Our paper contributes to the extensive literature that analyzes 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). Unlike the earlier work, we argue that the scale of active management should be remeasured, and one needs to combine institutional AUM and retail AUM under the same strategy in order to accurately estimate the influence of scale on performance.

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 is different in that we emphasize the implications of institutional assets on drawing conclusions of mutual funds.

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. These funds function as open-ended vehicles, meaning the number of shares in the fund can increase or decrease based on investor activities. On the other hand, 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 designed for retail investors. At the end of 2022, households held 89% of US mutual fund assets (ICI Fact Book, 2023). Conversely, IVs predominantly cater to institutional investors and affluent individuals.[8] The Investment 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). Regarding reporting practices, GIPS requires that managers handling multiple portfolios with comparable investment strategies present their performance within a unified composite index,

[8]Scenarios do exist where institutional investors favor mutual funds over IVs, particularly when the convenience of a mutual fund outweighs the customization benefits. Mutual funds circumvent investors' exposure to the administrative costs associated with establishing an account, encompassing dealings with custodians, legal procedures, audits, and, in the case of foreign investments, interactions with market authorities, tax experts, and regulatory bodies. Smaller institutional investors might deem these administrative expenses prohibitive, leading them to opt for mutual funds.

reflecting the weighted average performance of its constituent portfolios. That is, 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, a mutual fund can be derived from a consistently outperforming IV. These paired entities, commonly referred to as "twins," are not limited to mutual funds and IVs; they could also encompass mutual fund twins targeted at disparate retail and institutional clientele.

Practitioners affirm that performance disparities between twins remain nominal due to the shared portfolio manager and strategy, as well as the potential legal liabilities tied to performance deviations (Evans and Fahlenbrach, 2012). However, achieving absolute performance uniformity proves impractical. 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. As we intend to capture institutional assets under identical investment strategies, *we require institutional vehicles to have at least 99% return correlation with their twin mutual funds.* We will explain how we identify twin IVs of mutual funds in the next 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. Because neither institutional product database is comprehensive in terms of coverage, we combine the two in order to identify as many as possible of the twin IVs of 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.

We take the following procedure to form our sample of actively managed equity mutual funds. First, we use the Morningstar category to select US equity funds from Morningstar Direct. Second, 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." Third, a fund enters our sample only after its AUM exceeds $15 million in 2023Q1 dollars.[9] Once a fund enters into our sample, we keep the fund regardless of further 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).

The quality of the datasets is largely reliable. Based on the Morningstar website, a significant portion (90%) of the institutional products featured in Morningstar's database originate from firms compliant with the Association for Investment Management and Research (AIMR). This compliance framework ensures consistent and standardized reporting practices. Based on our conversation with eVestment, eVestment also has an internal process to identify possible manager input errors and the reports of institutional products from asset managers to eVestment are consistent with their public disclosures, e.g., client reporting and websites.

3.2 Linking IVs with mutual funds

We now explain how we identify twin IVs of mutual funds. The linkage of mutual funds and IVs in the Morningstar institutional product database is conducted through the Morn-

[9] We intend to exclude the tiny mutual funds, and our results are not sensitive to this threshold.

ingstar identifier "Morningstar StrategyID."[10] Based on Morningstar's description, StrategyID is constructed 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, for each product/strategy in its database, eVestment lists different forms of investment vehicles, including SMAs, CFs, CITs, and mutual fund share classes. This allows us to connect mutual funds with IVs underlying the same strategy.

We combine Morningstar and eVestment to capture as many as possible the twin IVs of mutual funds. It is worth emphasizing that there are mutual funds for which we could identify IVs both in Morningstar and eVestment databases. Because our mutual fund data is from Morningstar Direct and Morningstar is more recognized in the academic literature, we prioritize the use of the information reported in the Morningstar institutional product database. Only if the necessary information is missing in the Morningstar database, we use the information of IVs reported in eVestment.

Because institutional clients can request various portfolio restrictions or adjustments,

[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%.

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 be conservative in measuring twin institutional assets, we require the IVs to have at least 99% return correlation with their twin mutual funds. This requirement is more stringent than that in Evans and Fahlenbrach (2012), which only requires 95% return correlation to be classified as twins. The appendix provides more details of the matching process.

Table 1: **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.

	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

As we have emphasized, we want to make sure that the identified IVs are managed in the same way as their twin mutual funds. To justify the matching of IV-mutual fund twins, Table 1 compares the return correlation between IV-mutual fund twins with the average pairwise return correlation between share classes of the same mutual fund. We find that the average return correlation between mutual fund-IV twin is similar to the average pairwise correlation between share classes of the same mutual funds (0.999

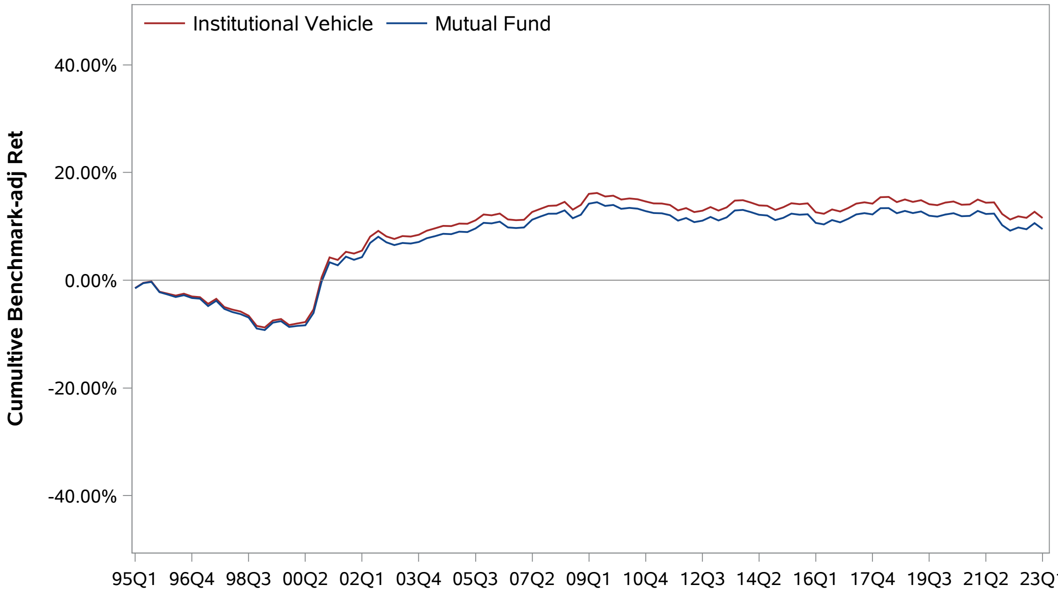
versus 0.999). In addition, the median return correlation between IV-mutual fund twins is already 100%, suggesting that the IV-mutual fund twins have almost identical return movements.

We further evaluate the differences in gross returns between mutual funds and their 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 pairs. Over the 28 years of our sample period, the average quarter return difference between the mutual fund-IV twins is only 1.7 bps. This is consistent with the finding of minimal return difference in Jones et al. (2022), who also use Morningstar Strategy ID to match twin IV and mutual fund. For example, in Table 9 of Jones et al. (2022), the estimated average gross-fee return difference between equity mutual funds and their twin IVs is about 2.5 bps per quarter.[11]

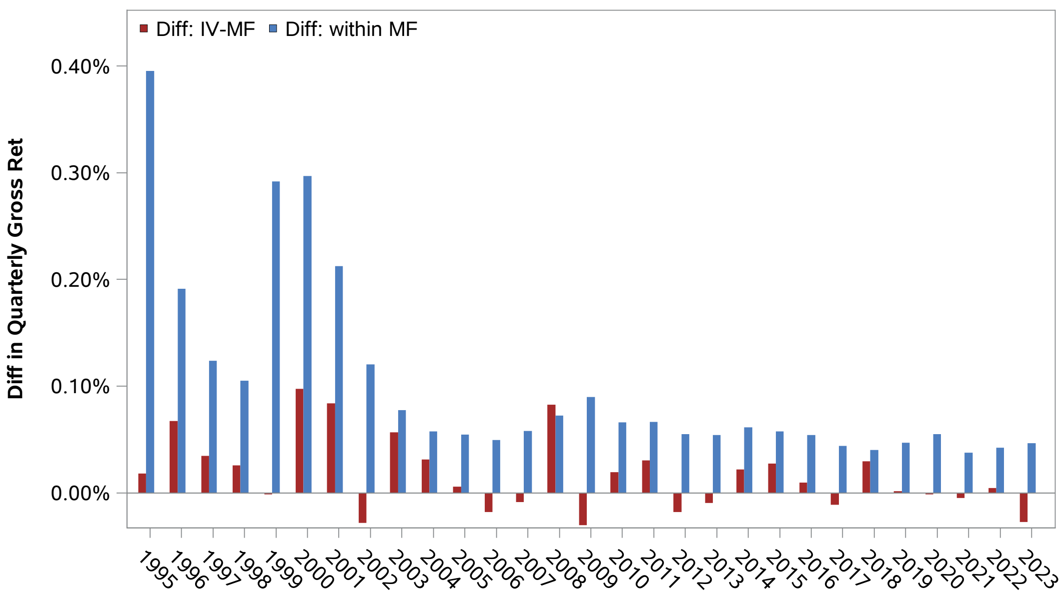
Panel B of Figure 2 further shows that, over most of the quarters in our sample period, the average difference in gross returns between mutual fund-IV twin is actually smaller than the average range of gross return differences among share classes of the same mutual fund. Researchers often combine assets of different share classes of the same mutual fund as these share classes are managed together. In this sense, these institutional assets should also be included in measuring the scale of an active strategy.

It is also of interest to compare mutual funds with and without twin IVs. Table 2 contains the such information. We find that larger mutual funds are more likely to have

[11] Jones et al. (2022) do not set the 99% return correlation threshold.



(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.

IVs offered. 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. On the other hand, the fund families with or without institutional products are similar in their total assets under management.

Another striking pattern in Table 2 is that mutual funds with IVs offered perform better than other mutual funds by about 24 to 32 basis points (bps) per quarter. This is also consistent with Evans and Fahlenbrach (2012), who find that retail funds with institutional twins outperform other retail funds, and with Gerakos et al. (2021), who find that institutional products outperforms mutual funds on average. In addition, we find tht mutual funds with IVs offered typically charge lower expense ratio to the mutual fund investors.

Table 2: **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.

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

It is acknowledged that IVs and mutual funds exhibit differences, encompassing aspects like managerial fiduciary duty, sensitivity of flows to returns, and the level of shareholder activism. Despite these differences, twin IVs hold trillions in assets and are pivotal in the realm of active asset management. Since these IVs adhere to the same investment strategy as their twin mutual funds, their assets significantly determine security selection and asset allocation, and possibly generate large price impact and transaction costs. Our focus is the influence of these twin IV assets on mutual fund trading and return performance.

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.

4 Remeasuring scale in active management

In this section, we show that at least 65% more total assets should be included in measuring the scale of active management.

Columns (1) and (2) of Table 3 show the number of active equity mutual funds in Morningstar Direct and the total assets in these mutual funds at the end of each year. Columns (3) to (8) present a summary of the subset of active equity mutual funds for which twin IVs are identified based on the Morningstar institutional product database. Columns (6) to (8) show the subset of mutual funds for which twin IVs are identified based on the eVestment database. Columns (9) to (11) show the subset of mutual funds for which twin IVs are identified based on either the Morningstar or eVestment database.

Table 3: **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

One can see that by combining the two datasets, the coverage of institutional assets increases by about 15% to 20% relative to each individual dataset. As we explained in Section 3.2, we prioritize the use of institutional assets reported in the Morningstar database, and when such information is missing, we use the assets reported in eVestment.

When our sample starts in 1995, 549 out of the 1428 actively managed equity mutual funds in Morningstar Direct have twin IVs identified based on the 99% return correlation standard. These IVs manage in total $210 billion assets, which is 25% of the total assets managed by active equity mutual funds. This ratio increased steadily over time to close to 66% in 2008 and has stayed relatively stable since then. When our sample ends in 2023, 1379 out of the 1954 active equity mutual funds have IVs identified based on the 99% return correlation threshold. These IVs manage $3.37 trillion assets in total, which is 65.8% of the total assets managed by active equity mutual funds. In an average year over our sample period, 56.4% of active equity mutual funds offer almost identical investment vehicles to institutional investors. These twin assets are managed together with their mutual fund counterpart and thus should be included in the scale measure if one intends to understand the influence of scale on return performance.

Next, we analyze the relationship between mutual fund assets and the assets in their twin IVs. Panel A of Table 4 shows that mutual fund assets and institutional assets under the same investment strategy are highly correlated. Specifically, one dollar increase in mutual fund asset is, on average, associated with 0.66 dollar increase in the twin IV assets. 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.

Table 4: **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. Panel B reports results from quarterly time-series regression. 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. *t*-statistics are computed with Newey-West correction of 4 lags.

Panel A: Fund Size		
DepVar: AUM_IV	(1)	(2)
AUM_MF	0.672***	0.663***
	(4.37)	(4.64)
Fund FE	N	Y
No. Obs.	87,841	87,832
Adj. R^2	0.549	0.858
Panel B: Industry Size		
DepVar: IndustrySize_IV	(1)	
IndustrySize_MF	1.042***	
	(4.67)	
No. Obs.	113	
Adj. R^2	0.487	

Following Pástor et al. (2015), we also measure the industry size of mutual funds (the twin IVs) by using the total mutual fund assets (the total twin IV assets) as a fraction of the total stock market capitalization. Panel B of Table 4 reports the relation between the industry size of mutual funds and the industry size of twin IVs. Similar to the fund-level results, the two industry size measures are highly correlated, although the R^2 is slightly lower (48.7%).

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 the next section.

5 Case study 1: diminishing returns to scale of active strategy

In the next two sections, we illustrate the importance of accurately measuring the scale of active management through two case studies. In our first case study, we revisit the estimate of fund-level and industry-level diminishing returns to scale (DRS) of active management by including assets in the twin IVs of mutual funds.

While earlier research of DRS uses pooled ordinary least square (OLS) panel regression (e.g., Chen et al., 2004; Yan, 2008; Ferreira et al., 2013), the estimates are unreliable due to the endogeneity caused by unobserved managerial skill. This endogeneity issue could be resolved by including fund fixed effects. As explained in Pástor et al. (2015), however, controlling for fund fixed effects can also introduce finite-sample biases. Thus, Pástor et al. (2015) propose a novel 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 both fund-level and industry-level DRS. 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. In order to make the analysis more comparable with the earlier work, we restrict our analysis to the same sample period as Zhu (2018), which is from 1995 to 2014.

Table 5 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 barely 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 avoid the omitted-variable biases.

Table 5 also shows the results of industry-level DRS. Here, the industry size of mutual funds is the fraction of mutual fund assets relative to the aggregate market, and the total industry size also includes the twin IV assets in the numerator. Once institutional assets under the same strategy are included, the industry-level DRS coefficients drop by about 30% to 50% depending on specifications. For example, the industry-level DRS coefficient changes from −0.0197 to −0.0132 under fixed-effect regression, indicating an overestimation of 49.2%, and it changes from −0.0189 to −0.0130 under recursive demeaning, indicating an overestimation of industry-level DRS by 45.4%. In addition, the conclusions are similar whether we use gross-fee returns or net-fee returns.

Table 6 conducts similar exercises in Table 5 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.

Table 5: **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		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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 6: **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 5.

Panel A: Dollar AUM_MF										
DepVar:	Benchmark-adj GrossRet					Benchmark-adj NetRet				
Regression Method:	FE		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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		RD	RD1	RD2	FE		RD	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

In summary, failing to include institutional assets under the same investment strategy of mutual funds can significantly bias the estimates of fund-level and industry-level DRS. These results suggest that active management actually has more capacity than previously estimated.[12]

6 Case study 2: dollar value added of active strategy

In our second case study, we revisit the prior work that studies whether active portfolio managers can extract value from the capital markets.

Berk and Van Binsbergen (2015) suggest that alphas of active funds only measure the rationality of investors and the competitiveness of the financial market rather than the skill level of active fund managers. In contrast, they propose the concept of dollar value added, which is the dollar value a fund extracts from the financial markets. In measuring realized dollar value added, Berk and Van Binsbergen (2015) use a fund's gross excess return over its benchmark multiplied by the assets under management (AUM) and find evidence of persistence in value added of active equity mutual funds.

Clearly, the dollar value added of an active investment strategy should include both the value added from mutual fund vehicles and the value added from institutional investment vehicles. Thus, the prior estimate based solely on mutual fund assets is incomplete, calling

[12] 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.

for a reexamination of the previous conclusion. We fill the gap in this section.

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

Table 7: **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

To set the stage, Table 7 reports the distribution of realized dollar value added with and without including assets in the twin IVs from 1995 to 2023. Based on our sample, the average dollar value added across all the fund-quarter observations is \$0.58 million ($t = 1.23$) without institutional assets, and it increases to \$1.71 million ($t = 2.94$) based on 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.

We then study the persistence of dollar value added, and the exercise closely follows Berk and Van Binsbergen (2015). Specifically, at each quarter end, we compute the average historical value added for each fund using quarterly value added over its entire history. We then sort the funds into deciles by their average historical value added and hold the funds in each decile over the next h years ($h = 3, ..., 10$). We then compute the average value added across funds in each decile and examine whether the top decile outperforms the bottom decile in terms of value added over the next h years. After that, we get a time series of dummy variables indicating whether the top outperforms the bottom. Finally, we perform a binomial test against the null hypothesis: the probability of the top outperforming the bottom is 50%. p-values are calculated based on the cumulative distribution function of the binomial distribution.

Table 8 reports the results. Columns (1) and (2) in Panel A show that if one only uses mutual fund assets, the top decile of funds by historical dollar value added continues adding more dollar value than the bottom decile of funds with 55.86%, 57.66%, and 54.95% probability over the next three to five years, respectively. One can reject the null hypothesis of identical dollar value added between the two extreme deciles with a 90% confidence level for up to five years. However, one can not reject the null hypothesis of identical value added between the two deciles over longer horizons.

Table 8: **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

Columns (3) and (4) show the results by further including assets in the twin IVs. If we measure value added at the strategy level, i.e., including both mutual fund assets and IV assets, dollar value added becomes more persistent. For example, the top decile of funds by historical dollar value added continues extracting more value from the markets than the bottom decile of funds with 59.46%, 61.26%, and 59.46% over the future three to five years, respectively. The p-values are 1.11%, 0.38%, and 1.12%, respectively. Even at the eight-year horizon ($h = 8$), one can still reject the null hypothesis with a 90% confidence level. In other words, dollar value added becomes more persistent when the scale of a strategy is measured properly. These findings are expected in that active strategies actually have more capacity than previously estimated due to the smaller magnitude of DRS at both the fund level and industry level. Based on the logic of Berk and Van Binsbergen (2015), our results further strengthen their argument that active portfolio managers indeed have the skills to extract rents from the capital markets.

While we only conduct two case studies, we argue that this paper has much broader implications: our findings indicate that the flow metric of active management used in the literature is also incomplete. Likewise, fixed-income mutual funds are subject to the same measurement issue, as well as passively managed investment vehicles. For example, Chinco and Sammon (2023), based on trading volume, infer that passive ownership is twice as large as 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, the total size of passive institutional products is, on average, 80% of the total assets of passive mutual funds and ETFs.

7 Conclusion

This paper makes one simple point: the scale of active management needs to be reassessed. By combining two major datasets on institutional investment products, we identify trillions of institutional assets that are managed under the same investment strategy as their twin mutual funds with a return correlation higher than 99%. Because assets in these institutional vehicles adhere to the same investment strategy and thus influence 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 of 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 overestimates fund-level and industry-level diminishing returns to scale by up to 90% and up to 50%, respectively, suggesting that active strategy has more capacity than previously thought. We also find that the dollar value added of active strategy is on average higher and more persistent than prior estimates, supporting the argument that active portfolio managers have the skills to extract rents from the capital markets.

As scale has become a standard control in the analysis of managerial skill, trading behaviors, and return performance of mutual funds, we believe that the simple point of this paper has broad implications on the extensive mutual fund literature.

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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;[13] (*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.[14]

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

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

[14]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.

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 index trackers.[15] 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

[15] 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).

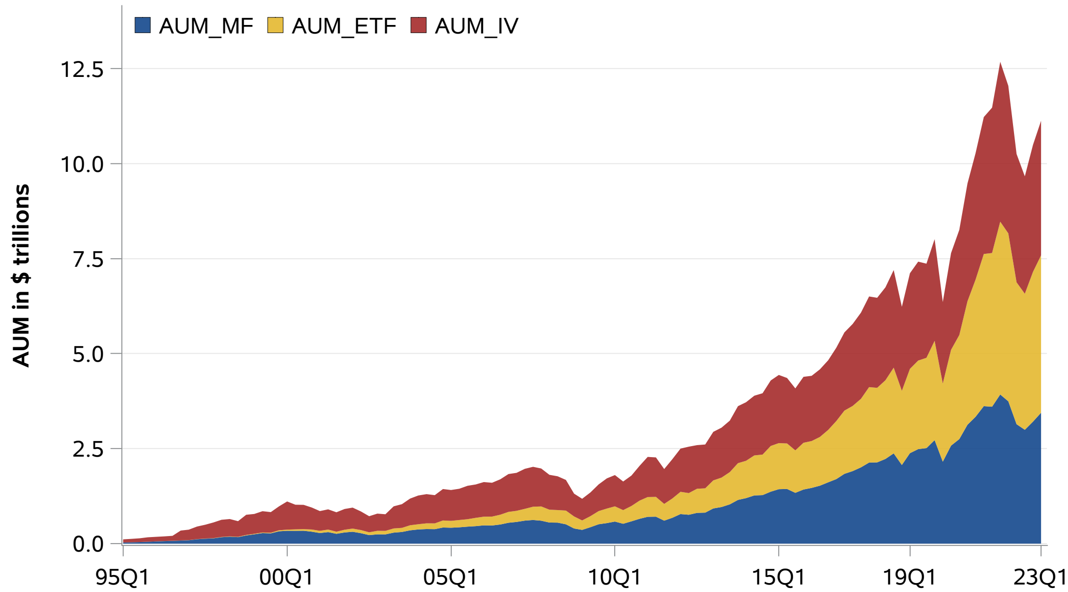

Figure B.1: **AUM of passive mutual funds, ETFs, and institutional vehicles.** This figure shows the AUM (in $ trillions) of passive equity mutual funds, equity ETFs, and passive equity separate accounts in each quarter.

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 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.[16]

[16]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