

# Remeasuring Scale in Active Management\*

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## Abstract

We argue that 65% more total assets should be included in the scale measure of actively managed portfolios. By leveraging two major datasets of institutional products, we identify trillions of institutional assets that are co-managed with their “twin” mutual funds with average return correlations of 99.9%. By including these institutional assets, fund-level (industry-level) diminishing returns to scale of active investments is reduced by up to 90% (70%), and the dollar value added of active strategies is more substantial and persistent than previously suggested. Besides skewing crucial estimates in active asset management, the measurement issues extend to flow metrics and passive investments.

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# 1 Introduction

Since the seminal work of Berk and Green (2004), a large empirical literature has been devoted to investigating the relationship between scale and return performance of actively managed mutual funds (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 key 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; Ben-David et al., 2022a). Thus, accurately measuring scale is crucially important for the extensive research on active investing and asset management.

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, trading, 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 U.S. equity mutual funds in any given year have corresponding “twin” institutional vehicles (IVs), which are offered to institutional investors in the forms of separately managed accounts (SMAs), collective investment trusts (CITs), or commingled funds (CFs).<sup>1</sup> 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%).<sup>2</sup> When our sample starts in 1995, the twin IVs 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.

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<sup>1</sup>Note that SMAs, CITs, and CFs are different from institutional share classes 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.

<sup>2</sup>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.

When our sample ends in 2023, the assets in the twin IVs have reached \$3.37 trillion, which is equivalent to 65.8% of the total active domestic equity mutual fund assets.

As assets in these IVs are co-invested with their twin mutual funds, it is evident that these IV assets have a significant impact on security choice and asset allocation, generate price impact, and incur transaction costs.<sup>3</sup> 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.<sup>4</sup>

We demonstrate omitting assets under management of twin IVs can severely skew crucial estimates in asset management research. To illustrate this point, we show that this oversight leads to an underestimation of the capacity for active management and an underestimation of the value added by active funds' portfolio managers. Specifically, we find that estimates on diminishing return to scale can be significantly inflated. When incorporating the AUM from twin IVs into the scale metric, the negative relationship between scale and performance is overstated by up to 90% at the fund level and up to 70% at the industry level (Pástor et al., 2015; Zhu, 2018), revealing a substantial underestimation of the actual capacity for active management. Furthermore, by integrating twin IV assets, we ascertain that active portfolio managers possess much larger average dollar value added than previously estimated; we also show that dollar value added has

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<sup>3</sup>Pástor et al. (2020) provide an elegant theory that explains how scale affects portfolio managers' investment process.

<sup>4</sup>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.

much greater persistence, reinforcing the argument that portfolio managers have the skill to extract economic rents from financial markets (Berk and Van Binsbergen, 2015).

Besides demonstrating the significance of accurate scale measurement through two specific examples, our findings also indicate that the flow metrics utilized in previous studies are not comprehensive for certain purposes. For instance, we find that the aggregate capital outflow of active management is at least 63% higher than previously estimated. Furthermore, the pervasive nature of this measurement issue extends beyond the realm of 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 based on trading volume. We find that the majority portion of the “missing” passive shares are actually held in passive institutional products.<sup>5</sup>

This paper is organized in three 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.<sup>6</sup> Because neither database is comprehensive in terms of coverage, we combine the two databases to identify as many of the twin IVs of mutual funds as possible. Specifically, 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 SMAs, CITs, or CFs to their mutual fund equivalents. This allows us to connect mutual funds with their twin IVs.

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<sup>5</sup>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).

<sup>6</sup>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.

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 a 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 domestic equity mutual funds in Morningstar Direct,<sup>7</sup> 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 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 trillion in assets, amounting to 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

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<sup>7</sup>A mutual fund enters our sample only after its AUM exceeds \$15 million.

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.

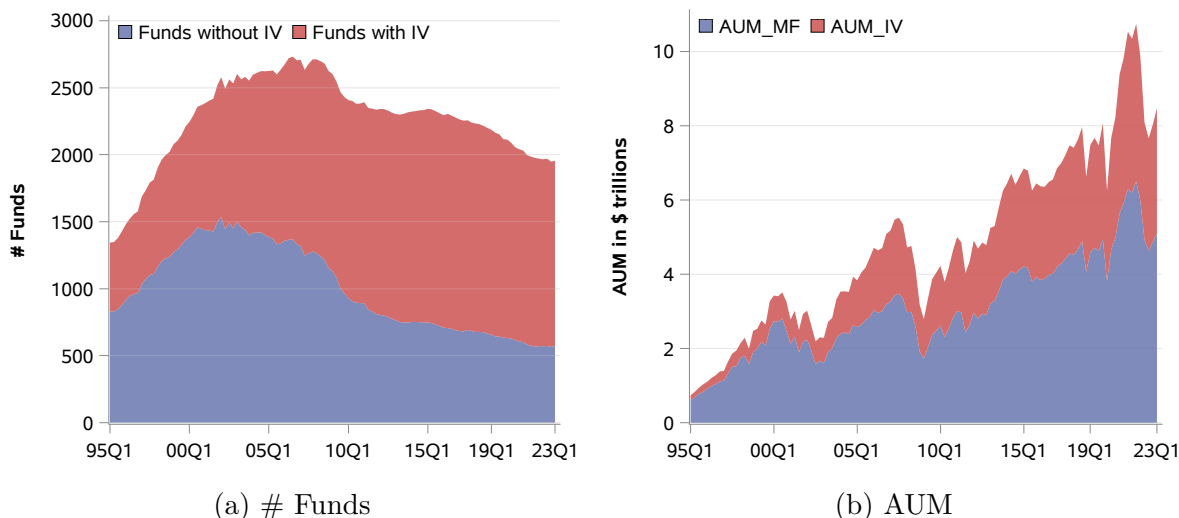


Figure 1: **Summary of active equity mutual funds and twin IVs.** Panel (a) plots the number of active equity mutual funds with and without IVs identified in each quarter. Panel (b) plots the aggregate AUM of mutual funds and aggregate AUM of the twin IVs. The sample period is from Q1 1995 to Q1 2023.

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 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 as well as the recursive de-mean (RD) approach pioneered by Pástor et al. (2015) and further refined by Zhu (2018) to estimate both fund-level and industry-level DRS. 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 70%. 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 \$1.75 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, we find that the persistence of 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.

After demonstrating the implications of IV assets on crucial estimates in prior research of active asset management, in the third part of the paper, we further investigate flows of actively managed IVs. At the aggregate level, we document that institutional investors have been withdrawing capital from these identified active IVs since the mid-2000s, to-

taling \$1.9 trillion dollar at the start of 2023. This pattern mirrors the aggregate capital outflow of active equity mutual funds. Over the same period, retail investors have taken a total of \$3 trillion in capital out of actively managed mutual funds. As a result, the total outflow from active investment strategies is at least 63% higher than previously estimated. Thus, it is imperative to include these IV flows in order to assess the economic impact of the shrinking active asset management (e.g., Stambaugh, 2014; Sammon, 2024).

In the cross-section, we find that the variation of IV flows is largely independent of that of their twin mutual funds, as reflected by the low  $R^2$  of mutual fund flows in explaining the twin IV flows. In addition, IV flows are less responsive to past performance relative to mutual fund flows, and the IV flow-performance sensitivities remain stable across different market states, in contrast with the hump-shaped sensitivity patterns seen in mutual fund flows (Franzoni and Schmalz, 2017). We also find that institutional investors do not exhibit style-chasing behaviors, in contrast to mutual fund investors who respond strongly to style-level performance.

Facing these relatively more “patient” institutional investors, we find that mutual fund managers offering twin IVs tend to have longer investment horizons and keep their positions longer than other mutual fund managers, which behavior is found to be generally associated with superior performance (Lan et al., 2023). That IV flows can significantly influence portfolio choices further supports our argument of including IV assets and IV flows in the scale and flow metrics of actively managed portfolios.

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. Given that scale is a key variable in analyzing managerial skill, trading behaviors, and the return performance of portfolio managers, the primary insight of this paper also has far-reaching implications for the extensive body of asset management literature.

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 the 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 portfolio 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 investigates IV flows and compares flows of mutual funds and their twin IVs. Section 8 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 (See Figure 3.2 of the 2023 ICI Fact Book). If one excludes money market mutual funds, households held 94.2% of US mutual fund assets as of 2022. In contrast, IVs predominantly cater to institutional investors and affluent individuals.<sup>8</sup> The Investment Company Act of 1940 mandates that mutual funds must daily price their shares and disclose their performance to their investors. In stark

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<sup>8</sup>There are instances where institutional investors prefer mutual funds over IVs. 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.

contrast, there is no equivalent obligation for institutional investment products at large. In fact, the disclosure practices of IVs 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 (Gerakos et al., 2021).

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 the 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.

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). 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 integrate 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.<sup>9</sup> 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, 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

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<sup>9</sup>This threshold is set to omit very small mutual funds, and we find that our results are robust to this criterion.

through the Morningstar identifier “Morningstar StrategyID.”<sup>10</sup> 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 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

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<sup>10</sup>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%.

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 \$4426 million, while the average AUM of mutual funds without IV offered is only \$1340 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 that mutual funds with IVs offered typically charge a 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 the 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 underperforms 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) and Gerakos et al. (2021), who find that institutional products outperform mutual funds on average. In Appendix Table C.2, we also estimate a logit model to estimate the probability of a mutual fund offering twin IV. Notably, larger mutual funds and those that have recently outperformed their benchmarks are more likely to offer institutional products.

### 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 2 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 2 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.<sup>11</sup>

**[INSERT FIGURE 2 HERE]**

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 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

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

assets managed under the same investment strategy.<sup>12</sup>

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 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 between mutual funds and 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 3 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

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<sup>12</sup>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.

database. In cases where this data is unavailable, we supplement our analysis with the assets reported in the eVestment database.

**[INSERT TABLE 3 HERE]**

At the onset of our sample in 1995, out of 1428 actively managed domestic 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  $3 \times 3$  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.

We move on to investigate the correlation between assets in mutual funds and those in their corresponding twin IVs. Table 4 illustrates this relationship, indicating a strong correlation between assets managed under the same investment strategy. Specifically, a one dollar increase in mutual fund assets is, on average, associated with a 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.

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. Column (5) of Table 4 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 48.3%.

[INSERT TABLE 4 HERE]

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 Scaling up: capacity of active management with twin IVs

In the subsequent two sections, we underscore the important implications of precise scale measurement 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). These estimates are unreliable due to the endogeneity issue arising from unobserved managerial skills. This endogeneity problem 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 both the fund fixed-effect regression and the refined RD approach of Zhu (2018) to estimate DRS at both the fund level and the industry level. Unlike 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.

Table 5 shows the estimation results for mutual funds with institutional twins. As one can see, by including the twin institutional assets, the fund-level DRS coefficient changes from  $-0.0474$  to  $-0.0248$  based on regression with fund fixed effects, suggesting an overestimation of fund-level DRS by 91.1%. Based on the RD approach, the fund-level DRS coefficient also changes from  $-0.151$  to  $-0.0788$ , indicating an overestimation of fund-level DRS by 91.6%. 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 5 also shows the results for industry-level DRS estimation. Here, the industry size of mutual funds is calculated as the ratio of the total 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 60% and 70% depending on the specification employed. For instance, under fixed-effect regression, the industry-level DRS coefficient shifts from  $-0.0308$  to  $-0.0191$ . This change suggests that prior estimates without institutional assets may have overestimated industry-level DRS by approximately 60.5%. Similarly, using the RD approach, the coefficient adjusts from  $-0.0343$  to  $-0.0199$ , indicating an overestimation of about 72.3%.

[INSERT TABLE 5 HERE]

It is also worth noting that these findings hold true regardless of whether we analyze gross-fee returns or net-fee returns. In Appendix Table C.3, we conduct similar exercises in Table 5 but expand to all mutual funds. We find that the fund-level and industry-level DRS are significantly smaller once the twin institutional assets are also included.

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

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<sup>13</sup>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.

## 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 managerial skill, which is basically 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. Berk and Van Binsbergen (2015) demonstrate evidence of persistence in value added by active equity fund managers.

Clearly, the dollar value added by 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 extracting values from the markets, applying the corrected scale measure that includes the assets of twin IVs.

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 Category Benchmark. These returns are calculated before deducting any fees.

To set the stage, Table 6 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 \$1.75 million ( $t = 2.99$ ) 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 6 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 ( $h = 3, \dots, 10$ ). 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 7 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 7 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%, 60.36%, 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.

Overall, Sections 5 and 6 highlight the significance of accurately measuring scale through two key metrics in active management. Yet, the implications of our findings on scale measurement surpass these instances to fixed-income mutual funds and passive investment vehicles. 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 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. In other words, the majority portion of the “missing” passive shares are actually held in passive IVs.

## 7 Institutional flows and implications

Having analyzed the implications of IV assets on some crucial estimates in active asset management research, in this section, we move on to investigate IV flows and compare them with mutual fund flows. Additionally, we demonstrate that institutional flows can influence fund managers’ portfolio choices, further reinforcing the need to include twin IV assets in scale metrics.

### 7.1 Understanding institutional flows

**Aggregate IV flows** We first study the aggregate flow of the identified actively managed IVs. Panel (a) of Figure 4 plots the aggregate flow of these IVs and the aggregate flow of their twin mutual funds each year from 1995 to the start of 2023. Up until around the financial crisis, both retail and institutional investors allocated net inflows to actively managed strategies. For example, from 1995 to 2007, institutional investors allocated a total of \$537.7 billion to those identified IVs, while retail investors allocated \$537.1 billion to their twin mutual funds.<sup>14</sup>

[INSERT FIGURE 4 HERE]

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<sup>14</sup>If we also include mutual funds without twin IVs, the total cumulative capital flow up to 2007 was \$560.6 billion.

It is widely known that retail investors have been withdrawing investments from actively managed equity mutual funds since about the 2008 financial crisis. We find the same pattern also applies to institutional investors as well (see Panel (b) of Figure 4). For example, since 2008, a total of \$1.9 trillion dollar has been withdrawn by institutional investors from the identified actively managed IVs, while retail investors have taken \$2.8 trillion dollar from their twin active mutual funds. Adding mutual funds that do not have twin IVs, the total cumulative outflow from active equity mutual funds is 3 trillion.

As a result, the total capital leaving active investments is at least  $1.9/3 = 63\%$  higher than previous estimates merely based on mutual fund flows. Thus, when assessing the economic impact of shrinking active investments (e.g., Stambaugh, 2014; Coles et al., 2022; Sammon, 2024), it is important to include these institutional capital movements so that one can get unbiased estimations.

**Compare cross-sectional IV flows and mutual fund flows** Next, we explore the cross-sectional relationship between flows of mutual funds and flows of their twin IVs. In Panel A of Table 8, we regress flows of IVs on flows of their corresponding twin mutual funds. We use both dollar flows and percentage flows in this exercise. While the regression coefficients are statistically positive, mutual fund flows can only explain a small fraction of variation in IV flows, as reflected by a low  $R^2$  of about 1% to 2% in the univariate regressions. Panel B of Table 8 further shows the relation between mutual fund flows and IV flows at the style level. The style-level dollar flows have a  $R^2$  of 3% and the percentage flows have a higher  $R^2$  of about 10% in the style-level regressions. Taken together, the results suggest that flows into these twin vehicles are largely independent of each other in the cross-section, especially at the fund level.

[INSERT TABLE 8 HERE]

We then explore how mutual fund flows and IV flows respond to past performance in Table 9. The unit of observation is fund-quarter. While IV flows do react positively to past performance, their responsiveness is less pronounced than that of mutual fund flows. For example, the coefficients in Columns (1) and (5) of Panel A indicate that the flow-performance sensitivity of mutual funds is about 50% higher than that of IVs (0.492 versus 0.326). This observation aligns with the findings of Evans and Fahlenbrach (2012), who also note a weaker responsiveness of institutional flows.

[INSERT TABLE 9 HERE]

Additionally, we also observe that the flow-performance sensitivity of IVs remains relatively stable regardless of overall market conditions (see Panel B of Table 9). This consistency stands in contrast to the hump-shaped sensitivity pattern seen in mutual fund flows, first documented by Franzoni and Schmalz (2017). That is, unlike mutual fund investors, who are more responsive to fund performance in moderate market states, IV investors do not exhibit significant differences in different market states.

In Panel C of Table 9, we further examine the flow-to-performance sensitivity at style level. While mutual fund flows show a significantly positive sensitivity to past style returns, such sensitivity is muted for IV flows. In other words, institutional investors do not exhibit style-chasing behaviors.

In short, the results in Table 8 and Table 9 indicate that, in the cross-section, IV flows are less sensitive to past performance and market conditions, and they tend to move independently relative to mutual fund flows.

## 7.2 Implications of institutional flows on portfolio choices

Facing these relatively more “patient” institutional investors, portfolio managers offering IVs could take longer horizon investments, which generally lead to superior performance (Lan et al., 2023).<sup>15</sup> To test this implication of IV flows on portfolio choices, we directly compare the investment horizons for mutual funds with and without IVs. Specifically, we follow Lan et al. (2023) to calculate the portfolio holding horizon, which measures the average length that a fund keeps its holdings until the fully liquidating date of the holdings. The results are reported in Table 10.

[INSERT TABLE 10 HERE]

We find the investment horizon of mutual funds with twin IVs is generally longer than that of mutual funds without IVs (by about 12 months based on the value-weighted investment horizon). This difference is larger if we measure the portfolio-level holding horizon using portfolio weights, suggesting mutual funds with twin IV hold their larger positions even longer. In addition, to make sure this pattern is not driven by differences in stock liquidity, we examine large-cap, mid-cap, and small-cap funds separately. We find similar results in those sub-samples of funds.

The findings in Table 10 are consistent with the conjecture that portfolio managers with more patient institutional investors can implement more “patient” investment strategies. Together with the documented strong positive association between fund investment horizon and performance in Lan et al. (2023), these findings contribute to the outperformance of funds with IV relative to funds without IV, as shown in Table 1, Appendix Table C.1, and in Evans and Fahlenbrach (2012).

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<sup>15</sup>We thank Richard Evans for suggesting this analysis.

In summary, this analysis of investment horizons demonstrates the existence of IVs can influence portfolio choices. It reinforces our argument that institutional assets should be included when examining the relationship between scale and various elements, such as trading activities, managerial skill, and return performance of active management.

## 8 Conclusion

This paper makes one simple point: the scale of active management should be re-assessed. 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 can significantly overestimate diminishing returns to scale at both the fund and industry levels—by up to 90% and 70%, respectively. This suggests that the capacity of active strategies is greater than previously assumed. We also 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.

Additionally, we also demonstrate that the measurement issues apply to flow metrics

and passive investment vehicles as well. Given that scale is a key variable in analyzing managerial skill, trading behaviors, and the return performance of portfolio managers, the primary insight of this paper has far-reaching implications for the extensive body of asset management literature.

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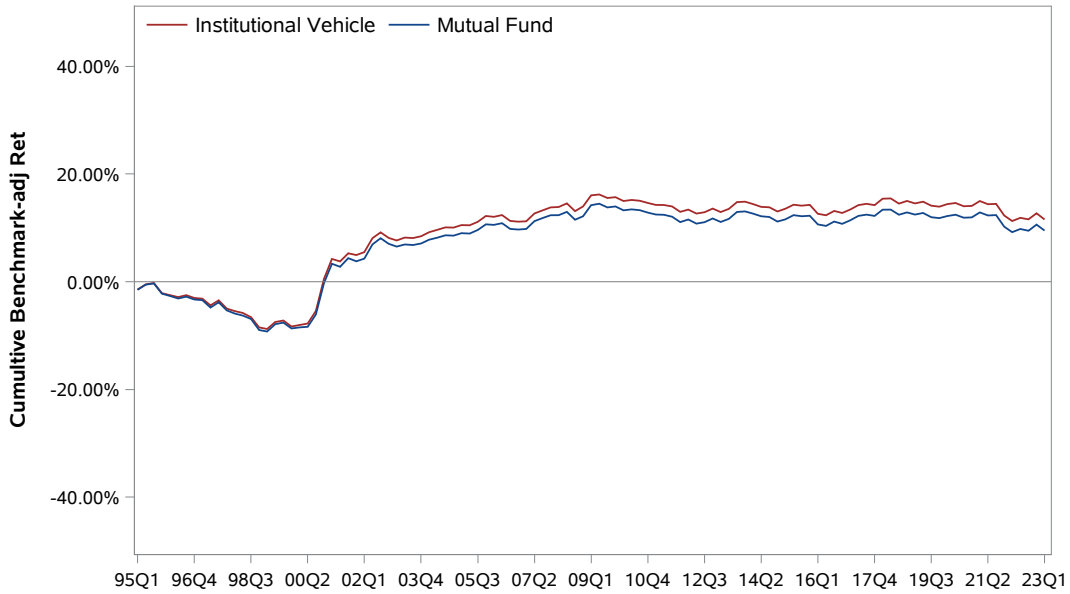
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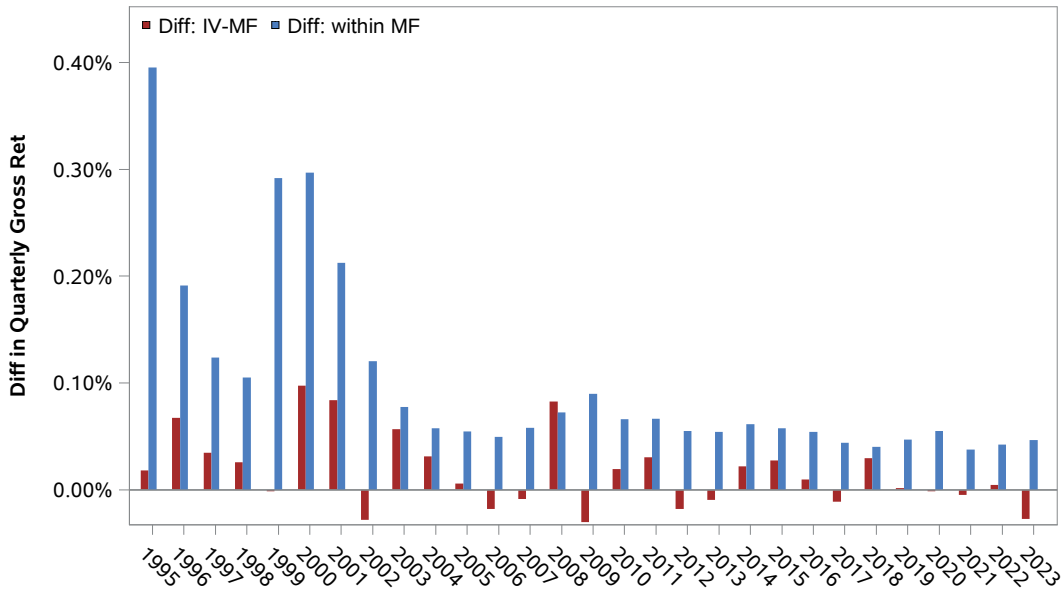
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(a) Cumulative returns adjusted by Morningstar category benchmark



(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.

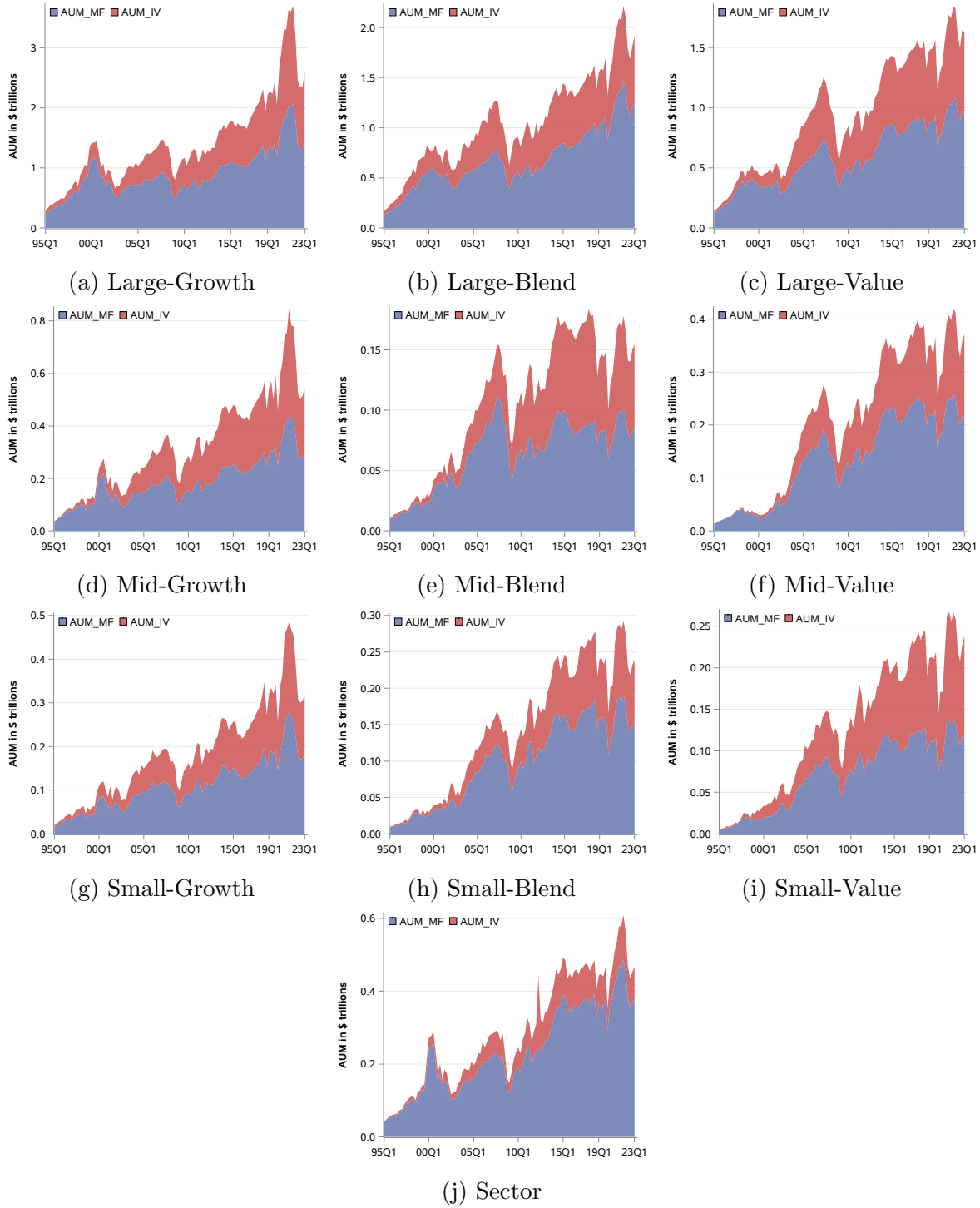
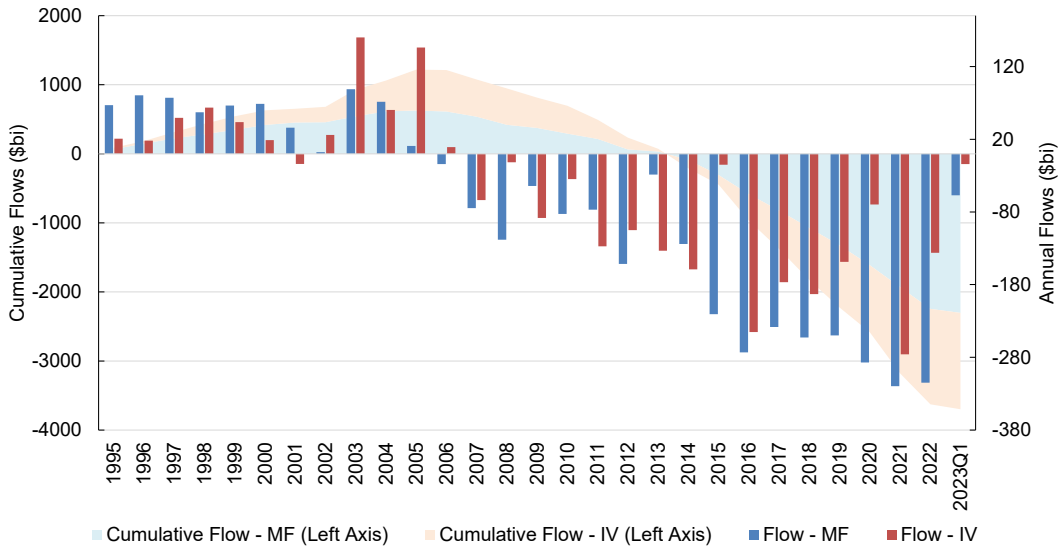
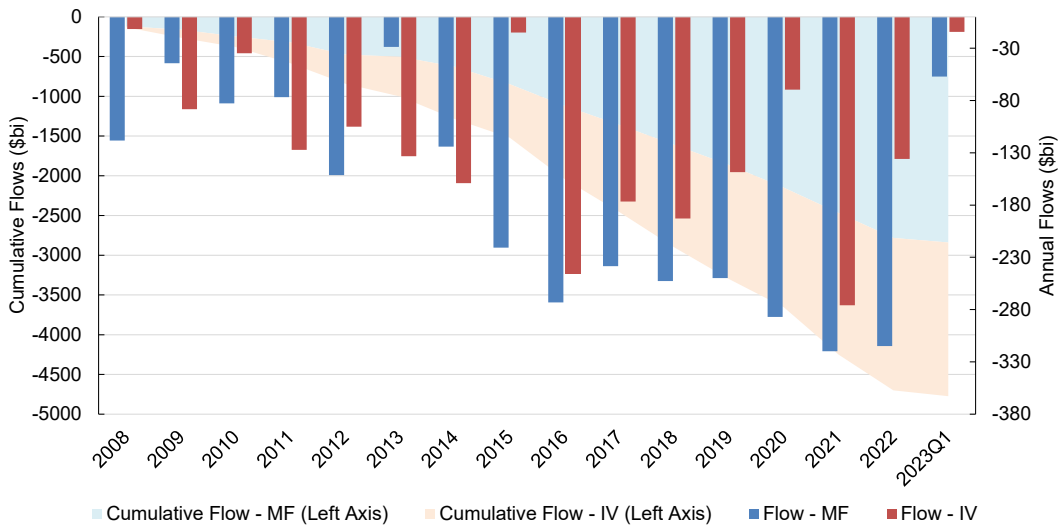


Figure 3: **Summary of active equity mutual funds and twin IVs by categories.** Panels (a) to (j) plot the aggregate AUM of mutual funds and aggregate AUM of the twin IVs by Morningstar categories. Categories in panels (a)-(i) correspond to the  $3 \times 3$  size-value style box in Morningstar, and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



(a) Sample period: 1995-2023Q1



(b) Sample period: 2008-2023Q1

Figure 4: **Cumulative and annual flows of mutual funds and twin IVs.** This figure plots the aggregate cumulative dollar flows and annual dollar flows of mutual funds and the twin IVs. The sample periods are 1995-2023Q1 and 2008-2023Q1 in panel (a) and (b), respectively. The sample includes all actively managed US equity funds that can be matched with twin institutional vehicles.

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.  $\beta_{Mkt}$ ,  $\beta_{SMB}$ ,  $\beta_{HML}$ , and  $\beta_{UMD}$  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)	1,340	4,426
AUM_Total (\$ mi)	1,340	7,301
Family AUM_MF (\$ mi)	99,424	97,464
Benchmark-adj Gret(%)	0.01	0.25
Benchmark-adj Nret (%)	-0.34	-0.02
Annual MF expense ratio (%)	1.29	1.11
MF_Return_Vol	0.054	0.052
$\beta_{Mkt}$	0.981	0.977
$\beta_{SMB}$	0.190	0.248
$\beta_{HML}$	0.005	0.042
$\beta_{UMD}$	0.004	0.001

**Table 2: 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. “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. “Share Classes (Avg)” refers to the average of pairwise gross return correlations within the same fund, and “Share Classes (Min)” refers to the minimum of pairwise gross return correlations within the same fund. “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). “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
MF&IV	0.999	0.002	0.991	0.996	0.999	1.000	1.000	1.000
Share Classes (Avg)	0.999	0.013	0.989	1.000	1.000	1.000	1.000	1.000
Share Classes (Min)	0.998	0.021	0.950	0.999	1.000	1.000	1.000	1.000
within Category	0.890	0.126	0.429	0.786	0.869	0.922	0.953	0.972
within Family-Category	0.938	0.069	0.667	0.861	0.924	0.958	0.980	0.995



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.

Fund Sample: Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	#Funds	All AUM_MF (\$ tn)	with IV from MS			with IV from eV			with IV from MS or eV		
	#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	510	0.69	0.55	662	1.25	0.46	785	1.37	0.58
1999	2210	2.52	548	0.94	0.72	709	1.64	0.60	845	1.80	0.76
2000	2370	2.48	590	0.94	0.74	773	1.61	0.63	923	1.76	0.79
2001	2517	2.19	646	0.87	0.68	847	1.48	0.59	1021	1.60	0.75
2002	2532	1.67	683	0.69	0.57	892	1.18	0.52	1081	1.27	0.64
2003	2553	2.28	726	0.99	0.95	950	1.66	0.87	1155	1.78	1.05
2004	2623	2.63	766	1.18	1.15	1007	1.97	1.10	1223	2.10	1.31
2005	2637	2.84	818	1.33	1.44	1058	2.17	1.36	1297	2.31	1.61
2006	2705	3.19	865	1.53	1.69	1118	2.47	1.59	1372	2.64	1.90
2007	2712	3.34	905	1.63	1.78	1171	2.60	1.66	1434	2.78	2.01
2008	2625	1.92	941	0.97	1.13	1193	1.49	1.04	1471	1.60	1.27
2009	2430	2.48	956	1.27	1.45	1183	1.94	1.26	1466	2.09	1.58
2010	2382	2.82	989	1.46	1.71	1193	2.18	1.45	1489	2.37	1.83
2011	2336	2.64	1040	1.42	1.61	1211	2.06	1.32	1525	2.26	1.71
2012	2313	2.90	1080	1.57	1.78	1214	2.26	1.47	1539	2.49	1.89
2013	2317	3.86	1115	2.09	2.24	1234	3.03	1.84	1570	3.33	2.40
2014	2333	4.13	1139	2.23	2.30	1236	3.22	1.99	1583	3.55	2.51
2015	2309	3.92	1154	2.12	2.33	1236	3.05	1.95	1587	3.36	2.53
2016	2277	4.01	1162	2.19	2.33	1232	3.12	1.97	1587	3.43	2.55
2017	2240	4.57	1148	2.50	2.65	1206	3.57	2.25	1555	3.91	2.91
2018	2200	4.07	1130	2.23	2.32	1199	3.16	1.99	1535	3.45	2.56
2019	2116	4.94	1089	2.75	2.82	1161	3.83	2.43	1481	4.19	3.13
2020	2041	5.63	1059	3.20	3.38	1131	4.35	2.92	1436	4.78	3.75
2021	1976	6.50	1038	3.68	3.80	1117	5.02	3.32	1409	5.51	4.25
2022	1949	4.88	1014	2.70	2.78	1101	3.70	2.50	1384	4.07	3.16
2023(Q1)	1954	5.11	1012	2.83	2.92	1097	3.89	2.68	1380	4.27	3.37

Table 4: **Relation between mutual fund AUM and AUM of twin IVs.** Columns (1)-(4) report the 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. Standard errors are clustered by funds. Column (5) reports the 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.

	(1)	(2)	(3)	(4)		(5)
DepVar:		AUM_IV			DepVar:	IndustrySize_IV
AUM_MF	0.6727*** (4.39)	0.6642*** (4.66)	0.6714*** (4.36)	0.6649*** (4.62)	IndustrySize_MF	1.042*** (4.67)
Fund FE	N	Y	N	Y	Intercept	-0.088** (-2.15)
Time FE	N	N	Y	Y		
No. Obs.	87,841	87,832	87,841	87,832	No. Obs.	113
Adj. R <sup>2</sup>	0.551	0.859	0.552	0.859	Adj.R <sup>2</sup>	0.483

**Table 5: Relation between scale and subsequent performance.** This table shows the estimation results of DRS at the fund level and industry level. The sample is fund-by-quarter observations for mutual funds with IV AUM available, 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  $\times$  quarter. RD stands for the recursive demeaning regression method of Zhu (2018). Standard errors in RD are clustered by funds. We also report  $R^2$  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.

<b>Panel A: Dollar AUM_MF</b>								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
FundSize_MF (Coef. $\times 10^6$ )	-0.0540*** (-7.03)	-0.0474*** (-6.55)	-0.1620** (-2.15)	-0.1510** (-2.16)	-0.0531*** (-6.95)	-0.0468*** (-6.49)	-0.1566** (-2.14)	-0.1461** (-2.15)
IndsutrySize_MF		-0.0308** (-2.53)		-0.0343*** (-5.63)		-0.0297** (-2.44)		-0.0329*** (-5.42)
First-stage $R^2$			0.04	0.04			0.04	0.04
<b>Panel B: Dollar AUM_Total</b>								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
FundSize_Total (Coef. $\times 10^6$ )	-0.0309*** (-7.29)	-0.0248*** (-6.67)	-0.0967* (-1.83)	-0.0788* (-1.87)	-0.0303*** (-7.19)	-0.0244*** (-6.60)	-0.0931* (-1.82)	-0.0758* (-1.86)
IndustrySize_Total		-0.0191*** (-4.05)		-0.0199*** (-9.78)		-0.0185*** (-3.92)		-0.0193*** (-9.51)
First-stage $R^2$			0.04	0.04			0.04	0.04
<b>Panel C: Ln(AUM_MF)</b>								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
Ln(FundSize_MF)	-0.0016*** (-14.07)	-0.0016*** (-14.65)	-0.0019*** (-12.95)	-0.0018*** (-13.02)	-0.0016*** (-13.81)	-0.0016*** (-14.39)	-0.0018*** (-12.65)	-0.0017*** (-12.72)
IndustrySize_MF		0.0000 (0.00)		-0.0282*** (-4.70)		0.0004 (0.03)		-0.0270*** (-4.51)
First-stage $R^2$			0.15	0.15			0.15	0.15
<b>Panel D: Ln(AUM_Total)</b>								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
Ln(FundSize_Total)	-0.0018*** (-14.65)	-0.0016*** (-15.74)	-0.0021*** (-11.99)	-0.0018*** (-11.54)	-0.0017*** (-14.45)	-0.0016*** (-15.63)	-0.0020*** (-11.82)	-0.0017*** (-11.37)
IndustrySize_Total		-0.0088* (-1.87)		-0.0177*** (-9.07)		-0.0084* (-1.78)		-0.0171*** (-8.81)
First-stage $R^2$			0.15	0.15			0.15	0.15

Table 6: **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	1.75
$t$ -statistic	1.23	2.99
Cross-sectional mean	-0.79	-0.63
$t$ -statistic	-2.09	-1.23
<i>Percentile values:</i>		
p1	-55.87	-82.38
p5	-17.06	-25.01
p10	-7.43	-10.90
p50	-0.23	-0.27
p90	5.32	9.15
p95	12.84	23.48
p99	54.60	87.41
Percent Value-added<0	0.61	0.60

**Table 7: Persistence of dollar value added.** This table analyzes the persistence of dollar value added following the method in Berk and Van Binsbergen (2015). 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 its entire 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 ( $h = 3, \dots, 10$ ). 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	60.36	0.66
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

Table 8: **Relation between mutual fund flows and IV flows.** Panel A reports results from regressing the dollar/percentage flows of twin institutional vehicles in a quarter (Dollar\_Flow\_IV/Pct\_Flow\_IV) on the contemporaneous dollar/percentage flows of the mutual funds (Dollar\_Flow\_MF/Pct\_Flow\_MF). Dollar flows are adjusted to the price level of 2023Q1. The sample period is 1995Q1-2023Q1, and the observations are at fund-quarter level. Standard errors are clustered by funds. Panel B reports results from regressing the style-level dollar/percentage flows of IVs in a quarter (Dollar\_Style\_Flow\_IV/Pct\_Style\_Flow\_IV) on the contemporaneous style-level dollar/percentage flows of the mutual funds (Dollar\_Style\_Flow\_MF/Pct\_Style\_Flow\_MF). Style-level percentage flows in a quarter is computed as the dollar flows in a style-quarter scaled by total AUM of funds in the style at previous quarter-end. Styles are defined as Morningstar Category, including size-value 3-by-3 categories plus sector equity. Standard errors are clustered by style.

<b>Panel A: Fund-Level Flows of IV and MF</b>								
DepVar:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dollar_Flow_IV				Pct_Flow_IV		
Dollar_Flow_MF	0.601*** (4.36)	0.599*** (4.30)	0.642*** (4.88)	0.636*** (4.74)				
Pct_Flow_MF					0.330*** (13.63)	0.319*** (13.10)	0.328*** (13.54)	0.309*** (12.62)
Time FE	N	Y	N	Y	N	Y	N	Y
Fund FE	N	N	Y	Y	N	N	Y	Y
No. Obs.	75,811	75,811	75,787	75,787	75,811	75,811	75,787	75,787
Adj. R <sup>2</sup>	0.008	0.009	-0.011	-0.010	0.017	0.019	0.045	0.047
<b>Panel B: Style-Level Flows of IV and MF</b>								
DepVar:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dollar_Style_Flow_IV				Pct_Style_Flow_IV		
Dollar_Style_Flow_MF	0.701*** (28.80)	0.597*** (6.66)	0.710*** (26.89)	0.586*** (4.83)				
Pct_Style_Flow_MF					0.626*** (20.19)	0.609*** (13.52)	0.623*** (20.06)	0.604*** (13.69)
Time FE	N	Y	N	Y	N	Y	N	Y
Style FE	N	N	Y	Y	N	N	Y	Y
No. Obs.	1,130	1,130	1,130	1,130	1,130	1,130	1,130	1,130
Adj. R <sup>2</sup>	0.030	0.027	0.023	0.019	0.107	0.114	0.103	0.110

Table 9: **Flow-to-performance sensitivity of mutual funds and IVs.** Panel A shows the flow-to-performance sensitivity of MFs and IVs at fund-level. We regress the percentage fund flows of MFs or IVs in quarter  $t$  on fund gross returns (GRet) or fund benchmark adjusted gross returns (AdjGRet) in quarter  $t - 1$ . We control for the assets of MF or IV at the end of quarter  $t - 1$  and include fund fixed effects and year-quarter fixed effects. The sample period is 1995Q1-2023Q1. In Panel B, 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 $\times$ Time. Panel C shows the style-level flow-to-performance sensitivity. The dependent variable is the percentage flows to a style in quarter  $t$ , and the dependent variable is the style returns in quarter  $t - 1$ . Styles are defined as Morningstar Category, including size-value 3-by-3 categories plus sector equity. Style return is computed as AUM-weighted average gross returns across funds in a style. Standard errors are clustered by style.

Panel A: Flow-to-Performance Sensitivity								
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MFs				IVs			
GRet	0.492*** (15.56)	0.477*** (15.21)			0.326*** (5.15)	0.307*** (4.96)		
AdjGRet			0.682*** (16.50)	0.649*** (16.14)			0.508*** (6.53)	0.473*** (6.21)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	N	Y	N	Y	N	Y	N	Y
No. Obs.	75,598	75,574	75,566	75,542	75,598	75,574	75,566	75,542
Adj. R <sup>2</sup>	0.027	0.063	0.027	0.063	0.004	0.035	0.004	0.035
Panel B: Market State and Flow-to-Performance Sensitivity								
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MFs				IVs			
GRet	0.407*** (10.49)	0.393*** (10.13)			0.291*** (3.72)	0.279*** (3.63)		
GRet $\times$ Moderate	0.330*** (5.23)	0.321*** (5.14)			0.134 (1.07)	0.110 (0.88)		
AdjGRet			0.589*** (11.58)	0.561*** (11.27)			0.467*** (4.96)	0.421*** (4.59)
AdjGRet $\times$ Moderate			0.335*** (4.12)	0.318*** (4.01)			0.147 (0.89)	0.187 (1.13)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	N	Y	N	Y	N	Y	N	Y
No. Obs.	75,598	75,574	75,566	75,542	75,598	75,574	75,566	75,542
Adj. R <sup>2</sup>	0.027	0.064	0.027	0.064	0.004	0.035	0.004	0.035
Panel C: Style-Level Flow-to-Performance Sensitivity								
DepVar:	(1)	(2)			(3)	(4)		
	Style-Level MF Pct.Flow				Style-Level IV Pct.Flow			
Gret.Style	0.372*** (4.33)	0.367*** (4.29)			0.068 (1.31)	0.063 (1.23)		
Time FE	Y	Y			Y	Y		
Style FE	N	Y			N	Y		
No. Obs.	1,130	1,130			1,130	1,130		
Adj. R <sup>2</sup>	0.209	0.223			0.029	0.028		

Table 10: **Mutual fund investment horizon.** This table compares the investment horizon of mutual funds with and without IVs. At each quarter-end, we split the mutual funds into two groups based on whether a fund has twin IVs at the quarter-end (With IV versus Without IV). We then compute the equal- or value-weighted average mutual fund investment horizon for the two fund groups over the next quarter. This table reports the time-series average of the investment horizon of the two groups, together with the difference, over the sample period of 1998Q1 to 2023Q1. Specifically, we follow Lan et al. (2023) to measure the investment horizon of mutual funds based on their portfolio holdings: For each mutual fund at each holding reporting date, we compute the holding horizon for each stock as the time gap between the initiation date of the position and the fully liquidating date of the position. Then, for each fund at each reporting date, we compute the portfolio weighted average of holding horizon as the fund-level holding horizon. Last, we conduct a style adjustment by subtracting the average fund-level holding horizon of each style from the original fund-level holding. We report the style-adjusted holding horizon in the number of months. In this table, we first report the results for the full sample of funds. Then, we split all mutual funds into large-cap, mid-cap, small-cap, and sector categories based on their Morningstar category classification, and we also report results for each category separately.

Category	Port Wght	Without IV	With IV	Diff	Diff <i>t</i> -Value
Full Sample	VW	14.6	26.4	11.7	(9.31)
	EW	-1.3	3.9	5.3	(9.91)
Large-Cap	VW	17.6	29.8	12.2	(7.42)
	EW	-0.9	3.8	4.7	(6.56)
Mid-Cap	VW	13.8	13.0	-0.8	(-0.74)
	EW	-2.0	3.2	5.2	(9.03)
Small-Cap	VW	8.7	17.8	9.1	(8.41)
	EW	-2.2	3.1	5.3	(7.76)
Sector	VW	7.3	19.2	11.3	(8.28)
	EW	-1.1	9.2	10.5	(10.93)



# 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 the 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 about 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 as 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 fund names in the CRSP Mutual Fund database to see 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 matches 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 product (involving 295 mutual funds), and (ii) an eVestment product could be matched with more than one Morningstar mutual fund (involving 57 eVestment products). 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;<sup>16</sup> (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.<sup>17</sup>

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 names contain keywords that imply they are in-

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<sup>16</sup>We define a mutual fund as a passive fund if it is flagged as an index fund in Morningstar or its name contains “Index.”

<sup>17</sup>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.<sup>18</sup> 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 year,

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<sup>18</sup>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).

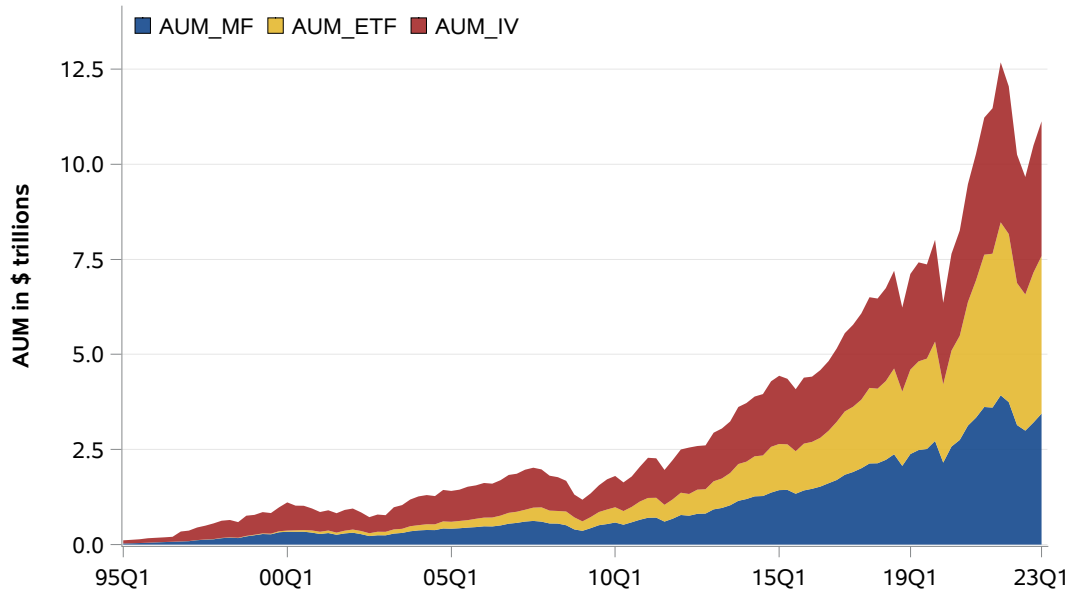


Figure B.1: **AUM of passive mutual funds, ETFs, and institutional vehicles.** This figure shows the AUM (in \$ trillions) of passive equity mutual funds, equity ETFs, and passive equity separate accounts in each quarter.

passive institutional products are about 80% of the total size of index mutual funds and ETFs. Table B.1 reports detailed statistics at each year-end.<sup>19</sup>

<sup>19</sup>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 the 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 underperforms the aggregate portfolio of mutual funds with twin IVs both before and after fees.

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 C.2. 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.

Table C.3 conducts similar exercises in Table 5 but expands to all mutual funds. Again, we 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  $-0.0747$  to  $-0.0423$  based on FE regression, suggesting an overestimation of fund-level DRS by 89.7%. The industry-level DRS coefficients change from around  $-0.0182$  to about  $-0.0124$  under various estimation methods. Similarly, if one uses the logarithm of the scale measure, the influence of IV assets happens to be neutralized.

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 three ways: (1) We use all active US equity mutual funds and use their lagged mutual fund plus twin IV AUM as portfolio weights (All Funds); (2) We use active US equity mutual funds without IVs and use their lagged mutual fund AUM as portfolio weights (Funds without IV); (3) We use active US equity mutual funds with IVs and use their lagged mutual fund plus twin IV AUM as portfolio weights (Funds with IV). 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.

<b>Panel A: Gross ret</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
	All Funds	Funds without IV	Funds with IV	All Funds	Funds without IV	Funds with IV
Alpha (annualized)	-0.192 (-0.50)	-1.128* (-1.67)	0.000 (0.02)	-0.204 (-0.59)	-1.236** (-2.03)	0.000 (0.01)
MKTRF	0.996*** (106.23)	0.992*** (51.48)	0.994*** (102.94)	0.985*** (106.50)	0.980*** (52.85)	0.984*** (119.65)
SMB				0.073*** (6.80)	0.117*** (6.81)	0.062*** (4.56)
HML				-0.007 (-0.58)	-0.059** (-2.58)	0.005 (0.37)
UMD				0.003 (0.37)	0.031* (1.91)	-0.002 (-0.20)
No. Obs.	339	339	339	339	339	339
Adj. R <sup>2</sup>	0.987	0.964	0.988	0.990	0.974	0.990
<b>Panel B: Net ret</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
	All Funds	Funds without IV	Funds with IV	All Funds	Funds without IV	Funds with IV
Alpha (annualized)	-1.104*** (-2.99)	-2.064*** (-3.10)	-0.888** (-2.46)	-1.116*** (-3.29)	-2.16*** (-3.56)	-0.888*** (-2.75)
MKTRF	0.997*** (106.18)	0.992*** (52.95)	0.994*** (102.91)	0.986*** (105.77)	0.980*** (53.30)	0.984*** (119.17)
SMB				0.073*** (6.60)	0.114*** (7.03)	0.061*** (4.47)
HML				-0.007 (-0.57)	-0.055** (-2.47)	0.005 (0.36)
UMD				0.003 (0.33)	0.029* (1.80)	-0.002 (-0.21)
No. Obs.	339	339	339	339	339	339
Adj. R <sup>2</sup>	0.988	0.966	0.988	0.990	0.975	0.990



Table C.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.

Reg Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit				OLS			
Log(MF_TNA)	0.2257*** (5.77)			0.1908*** (4.47)	0.0011*** (4.38)			0.0011*** (3.78)
MF_AdjGRet_P4	1.1489*** (4.51)			0.6391* (1.80)	0.0068*** (3.25)			0.0041 (1.47)
MF_Vol_P4	-1.9809 (-1.22)			-4.3010** (-1.99)	-0.0081 (-1.01)			-0.0251* (-1.91)
MF_Flow_P4	0.1370 (1.47)			0.1052 (0.89)	0.0012 (1.47)			0.0015 (1.13)
MF_Exp_Ratio	-204.2865 (-1.52)			-73.0371 (-0.46)	-0.5583 (-1.24)			0.1053 (0.13)
Log(MF_Age)	-0.1919** (-2.52)			-0.2507*** (-2.96)	-0.0009** (-2.20)			-0.0014** (-2.61)
Style_Ret_P4		0.2266 (0.92)		0.3392 (1.16)		0.0006 (0.21)		0.0018 (0.97)
Style_Flow_P4		2.4384*** (4.32)		-1.6329 (-1.67)		0.0356*** (2.97)		-0.0101 (-1.65)
Dummy_Large_Family			-0.4427*** (-3.86)	-0.0370 (-0.21)		-0.0063*** (-4.51)		-0.0000 (-0.03)
Dummy_Family_IV_Exist			1.0970*** (11.46)	0.4356*** (3.10)		0.0124*** (10.65)		0.0024*** (2.94)
Family_Flow_P4			-0.0007** (-2.00)	-0.0525 (-0.26)		-0.0000** (-2.21)		-0.0000*** (-4.37)
Family_Ret_P4			1.3580*** (3.92)	0.4949 (0.90)		0.0144*** (2.94)		0.0018 (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 <sup>2</sup> / Adj. R <sup>2</sup>	0.016	0.001	0.021	0.017	0.004	0.003	0.006	0.005

Table C.3: **Relation between scale and fund performance: all mutual funds.** This table performs the same regression analysis as in Table 5. The sample is based on fund-by-quarter observations of all mutual funds with or without IV.

Panel A: Dollar AUM_MF								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
FundSize_MF (Coef. $\times 10^6$ )	-0.0747*** (-9.33)	-0.0723*** (-9.40)	-0.1159*** (-2.71)	-0.1155*** (-2.77)	-0.0737*** (-9.27)	-0.0715*** (-9.33)	-0.1142*** (-2.72)	-0.1139*** (-2.77)
IndsutrySize_MF		-0.0182* (-1.91)		-0.0175*** (-5.91)		-0.0172* (-1.81)		-0.0165*** (-5.60)
First-stage R <sup>2</sup>			0.09	0.09			0.09	0.09
Panel B: Dollar AUM_Total								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
FundSize_Total (Coef. $\times 10^6$ )	-0.0423*** (-8.78)	-0.0381*** (-8.96)	-0.1121** (-2.08)	-0.0933** (-2.08)	-0.0416*** (-8.70)	-0.0375*** (-8.89)	-0.1086** (-2.07)	-0.0906** (-2.07)
IndustrySize_Total		-0.0124*** (-3.07)		-0.0121*** (-12.12)		-0.0119*** (-2.94)		-0.0116*** (-11.68)
First-stage R <sup>2</sup>			0.05	0.05			0.05	0.05
Panel C: Ln(AUM_MF)								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
Ln(FundSize_MF)	-0.0018*** (-14.77)	-0.0018*** (-15.50)	-0.0024*** (-18.42)	-0.0024*** (-18.41)	-0.0017*** (-14.51)	-0.0017*** (-15.23)	-0.0024*** (-18.80)	-0.0023*** (-18.85)
IndustrySize_MF		-0.0031 (-0.33)		-0.0121*** (-4.13)		-0.0024 (-0.26)		-0.0112*** (-3.85)
First-stage R <sup>2</sup>			0.12	0.12			0.12	0.12
Panel D: Ln(AUM_Total)								
DepVar:	Benchmark-adj GrossRet				Benchmark-adj NetRet			
Regression Method:	FE		RD		FE		RD	
Ln(FundSize_Total)	-0.0017*** (-14.25)	-0.0017*** (-15.59)	-0.0025*** (-18.13)	-0.0023*** (-16.72)	-0.0017*** (-14.01)	-0.0016*** (-15.32)	-0.0025*** (-18.54)	-0.0022*** (-17.22)
IndustrySize_Total		-0.0055 (-1.37)		-0.0092*** (-9.57)		-0.0051 (-1.28)		-0.0088*** (-9.16)
First-stage R <sup>2</sup>			0.10	0.10			0.10	0.10