Scale Economies, Bargaining Power, and Investment Performance: Evidence from Pension Plans*

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Abstract

We explore the relation between the size of a defined benefit pension plan and its choice of active vs. passive management, internal vs. external management, and public vs. private markets. We find positive scale economies in pension plan investments; large plans have stronger bargaining power over their external managers in negotiating fees as well as having access to higher (pre-fee)-performing funds, relative to small plans. Using matching estimators, we find that internal management is associated with significantly lower costs than external management, reinforcing the enhanced bargaining power of large pension plans that have fixed-cost advantages in setting up internal management.

Key words: Pension plans, active versus passive management, internal versus external asset management, power law, economies of scale, asset allocation, private versus public asset classes, investment performance

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1 Introduction

During recent decades, the professional asset management industry has undergone significant structural changes. The competitive landscape, influenced by both passive and active managers, has led to a substantial reduction in fees. Advancements in technology and increased availability of information have also played a role in this fee reduction (Blake et al., 2013). Furthermore, both active and passive managers have refined their investment offerings, focusing on specialization in their investment strategies. Simultaneously, major institutional investors like pension plans and endowments have expanded their allocations to alternative asset classes, including hedge funds, private debt, private equity, and real assets.

Defined-benefit (DB) pensions continue to play a significant role in the global financial market, with the total assets under management (AUM) of DB pensions experiencing substantial growth. Notably, state and local government DB plans in the U.S. have seen their AUM increase from \$1.4 trillion in 1995 to \$5.1 trillion in 2020, while private-sector DB plans in the U.S. have grown from \$1.5 trillion to \$3.4 trillion over the same period (Investment Company Institute, 2021, p. 177). Moreover, the DB landscape now includes several very large pension plans, such as CalSTRS, one of the world's largest pension funds, with total assets exceeding \$314.8 billion as of May 31, 2022.[1]

The confluence of the above-noted shifts in the asset management industry with the increased bulk of the largest DB plans brings several new issues to light, such as a potential increase in the bargaining power of DB plans in their interactions with their external money managers. Simply put, the negotiating power of very large DB plans, of late, may bring substantial changes in the balance of power between large DB plans and their investment managers.

To explore these issues, our study conducts a granular analysis of the DB industry, with an emphasis on the interaction of DB plan size with fees, asset allocation, and investment performance. For example, one economically important trend is that large DB plans are increasingly managing assets "in-house," to cut fees while potentially maintaining a reasonable level of performance (Beath et al., 2022).[2] A key issue that we explore is whether such in-house management brings greater bargaining power to plans when

[1] See https://www.calstrs.com/investment-portfolio

[2] As an important example, CalSTRS recently stated that in-house management and co-management with external managers has been instrumental to their cost savings (see link). However, remains unclear whether the choice of in-house management—or, the threat thereof—leads to greater negotiating power with external managers to obtain better pre-fee performance and/or lower fees.

they negotiate fees and shop for the best investment managers for external management services—and, whether such bargaining power mainly resides with the largest pension plans due to the fixed costs of establishing and maintaining internal management.

Our study brings a contrast to past research on funds with small-scale investors. In retail mutual fund markets, individual investors are usually considered as "atomistic" agents who have no individual (or collective) bargaining power. The seminal paper of Berk and Green (2004) (henceforth, BG) presents a model based on this assumption as well as the usual assumption that "alpha" generation by fund managers exhibits diseconomies of scale. Predictions from their model include that (1) skilled investment managers collect all of the rents from their alpha-generating efforts, (2) flows from atomistic investors occur at each period (in reaction to updated information about manager skills)—either into or out of each fund until management fees equal expected pre-fee alphas, and (3) all investors, being atomistic, obtain the exact same zero expected alpha, net-of-fees.

In the pension plan market that we examine, we propose that the only key assumption from the BG model that can be accepted without further investigation is the presence of pre-fee scale diseconomies in fund-level alpha generation. While retail markets may leave all bargaining power in the hands of asset managers, the situation is different for the largest pension plans. Given their substantial scale, these plans have the potential to negotiate favorable terms with external managers, including lower fees and access to well-performing managers. As a result, the economics of the largest plans may diverge from the BG model's zero expected alpha (net of fees) assumption, primarily due to their enhanced bargaining power. Accordingly, we explore the relationship between DB plan size, bargaining power, and the ability of large plans to capture value from external managers, whether through lower fees or higher pre-fee alpha generation by these managers.[3]

We also investigate the impact of scale in pension plans on asset allocation trends. For example, it is unclear whether the bargaining power of large plans results in a greater use of external active managers (presumably at lower fee levels) or a greater tendency to internally manage assets (either actively or passively). As another example, as large plans move assets to internal management, it is important to assess whether any potential reduction in their internal active management skills, compared to external managers,

[3]Of course, for internal management to pose a "threat" to external managers, there must be a large mass of plans that stand ready to manage internally—and, a finite mass of smaller plans, such that external managers do not retain all bargaining power, unlike the infinitely deep supply of capital assumed in BG. In this vein, we note that, while some large plans may choose not to spend the fixed costs of setting up internal management, the mere threat to do so gives them negotiating power with external managers.

outweighs the cost savings gained through internal passive management for different asset classes.[4] Thus, our paper provides a unique view into scale economies of plans and the associated bargaining power at the level of plan asset classes.[5]

The modeling framework proposed by Gârleanu and Pedersen (2018) (GP; henceforth), has parallels to the empirical setting of our analysis. In their model, investors incur a fixed search cost to identify skilled external asset managers who, in turn, incur a fixed cost from acquiring information about asset returns that enables them to outperform passive investments. Investment management fees in the GP model are determined through Nash bargaining, leaving a natural mechanism through which plan size (as a proxy for bargaining power) matters for fees as well as for net-of-fee returns when some investors are not atomistic in size. Further, information acquisition costs can be expected to be higher in the less transparent private asset markets than in public asset markets. This is consistent with an equilibrium in which investment management costs are relatively high in private asset markets, and the largest plans benefit disproportionately from their higher ability to engage with skilled managers, either due to their enhanced ability to overcome fixed search costs and/or to negotiate lower investment management fees once they identify skilled managers.

Two major trends drive our inquiry into scale-related performance in the pension fund industry. First, pensions have increasingly moved toward passive management of their public market exposures in both equities and (to a lesser extent) fixed-income investments. Second, pensions have increasingly turned to private equity funds or to direct investments in real assets as a source of diversification and higher long-term returns. These developments can be partially attributed to the shrinking number of publicly traded stocks that are available in the U.S., which is particularly relevant to large pension plans. In the face of these trends, as we will show, many large plans have assigned a greater role to internal asset management. Both of these trends are consistent with a shrinking level of fixed costs in setting up an internal asset management organization across all asset classes, but especially so in public market securities.

Our inquiry exploits a unique database to explore several dimensions of the pension plan sector, including both cross-sectional and time-series aspects. Our data is sourced

[4]That is, an important issue is whether internally managing a greater share of a plan's assets in a particular asset class leads to a different mix of active vs. passive management in that asset class, as well as other asset classes held by the plan. The role of pension plan scale in internalizing active vs. passive management can be expected to depend on the relative fixed costs of creating and maintaining an internal management organization for each, within a given asset class.

[5]For example, large pension plans may be more capable of actively managing private asset classes, where they might directly exert their size to obtain more favorable investments.

from CEM, a Toronto-based private consulting company that collects information from a diverse range of pension plans. Each year, CEM gathers data on these plans' asset allocations as percentages within major asset classes (e.g., public equities, fixed income, hedge funds, private equity, public debt, private debt, and real assets), asset subclasses (e.g., small-cap U.S. equities or infrastructure investments), and, within each subclass, their choice between active and passive management and between internal and external management. The CEM database uniquely includes data on AUM, gross returns, and investment costs for each subclass/active-passive combination. Additionally, the CEM staff routinely apply a battery of checks to obtain the most precise data possible.[6] We believe that the CEM data allows a closer look at the above questions than has been possible with prior studies.

With this CEM database, we find that large pension plans tend to invest a greater share of their plan assets in less-liquid sectors of the market, as well as sectors of the market where scale-related bargaining power can be expected to be especially important in achieving net-of-fee alphas, such as private equity investments (see also Dyck and Pomorski (2016)). Further, large plans tend to use internal management to a greater degree, particularly in public asset classes where the fixed-cost of establishing and maintaining internal investment management is lower.

Further, we identify two major shifts in the asset allocation of U.S. pension plans. First, the share of (publicly-traded) stocks and fixed income assets has declined from nearly 90% in the early 1990s to 70% at the end of our sample (2019), while allocations to non-traditional asset classes such as private equity, hedge funds, and real assets increase significantly over time.[7] Second, within traditional asset classes such as equity and bonds, we see large shifts toward more specialized mandates. For instance, there has been a transition from broad or all U.S. equities to funds focusing on large, medium, and small market capitalization segments in the equity space. Similarly, we observe a move from general U.S. bond allocations towards more specialized strategies targeting high-yield and credit objectives in the fixed-income sector. By far the biggest shift is toward international and global assets, which become more prominent over time, particularly in stock allocations.

These shifts in asset allocation are consistent with a decrease in the fixed costs of

[6] From our discussions with CEM, it is apparent that CEM researchers maintain frequent contact with their "subscribers" in cases where data looks suspect in order to maintain the data integrity.

[7] Hedge fund holdings, on average across plans, increase from 1% in 2003 to 6% in 2019. Private equity holdings also increase to 9% in 2019 from 4% in 2000; allocations to real assets increase to 10% in 2019 from 4% in the early 1990s.

managing investments, and this decrease varies widely across asset classes and sub-asset classes (as well as within an asset class or sub-asset class, between active and passive management).[8] When we examine the tendency of pension plans to manage assets internally, we find that plan size is of key importance. Larger plans are significantly more likely to manage assets internally in all asset classes except for hedge funds and multi-assets.

Upon further examination, we observe that the size of a pension plan negatively correlates with its tendency to employ active management, particularly for public securities, such as equities. Larger pensions increasingly harness the substantial economies of scale offered by passive management in public securities. This shift towards passive management is more pronounced over time, given the rapid decrease in fixed costs associated with passive management. This trend aligns with the diminishing capacity of larger plans to extract alpha from public securities markets, especially equities, as mentioned above. For the share of equities and fixed income that are managed externally, large plans are more likely to manage equities passively while preferring to manage fixed income investments actively, relative to smaller plans. Among internally managed assets, we find no significant association between plan size and choice of active vs. passive management—suggesting, perhaps, that diseconomies-of-scale in active management offset incremental cost reductions as the size of internal management grows.

Subsequently, we examine investment costs for our sample of pension plans by investment management mandate. Here, we find that the median cost of internally and passively managing stocks is 1-3 bps per year throughout the sample period, while internally and actively managed stocks bear a median cost that fluctuates between 5 and 11 bps per year. The median cost for externally and passively managed stocks hovers between 4 and 8 bps per year, while the median cost of external active management is noticeably higher—between 32 and 48 bps per year. For fixed income holdings, we observe similar patterns. Moreover, we find that external passive management costs have been decreasing over time for stocks and fixed income, converging toward the lower level of internal passive management costs. In contrast, we find no evidence of a convergence in the costs between internal and external active management for these asset classes or, indeed, for the private asset classes—consistent with a change in the composition of external actively managed mandates—i.e., a move toward more specialized strategies.

[8] The shift from public, broad asset classes to private or more-specialized public asset classes is consistent with Blake et al. (2013), who find that investment managers have moved to more specialized sub-asset-classes in seeking to provide value to pension sponsors. This is consistent with the increased competition in broad public asset classes that might be expected from a larger amount of aggregate investment money chasing a diminishing number of public securities.

We find strong evidence of significant economies of scale in investment management costs, and document that these follow a power law as a function of the amount of assets invested by a plan. The associated concave relation between investment management costs and plan holdings are particularly strong for public asset classes. Conversely, for the more labor-intensive private asset classes we find that it is more difficult to reduce average costs as plan size increases. We also find evidence of bigger economies of scale in fees for passively managed than for actively managed investments.

Plans' choice of management style (internal versus external and active versus passive) is likely to be endogenous in the sense that it depends on plan size and asset class characteristics. To account for such confounding effects (and, notably, control for plan size) and get a more direct estimate of the impact on plans' costs and return performance, we use a difference-in-differences approach that matches plans switching management style (e.g., from external to internal management) with similar plans that retain the same management style. We find strong evidence that plans' management costs unequivocally decrease when they switch from external to internal or from active to passive management, whereas costs increase when switching from internal to external or from passive to active management.

Our results for plan performance are as follows. First, for public asset classes, we find a modest association between plan size and net return performance, with the largest decile of plans (sorted by AUM) outperforming the smallest decile by about 20 bps per year. Next, we find that plan size matters more for alternative asset classes, where the top decile of plans outperforms the smallest decile of plans by about 200 bps per year.[9] Using our matching approach, we find significant evidence that plans' gross and (particularly) net return performance, controlling for plan size, improves among alternative asset classes following a switch from external to internal management, whereas return performance instead deteriorates following the reverse switch from internal to external management. For stocks and fixed income accounts, return performance (both gross and net of costs) improves for both transitions, i.e., from external to internal and from internal to external management. We attribute this to mean reversion in returns since poor prior-year returns is likely to cause a switch in management style. Finally, we find an insignificant effect on return performance for plans switching between active and passive management, consistent with managers setting costs so that the marginal plan is indifferent between active and passive management.

[9] These numbers are based on policy-adjusted returns. We explain in detail how these are constructed in Section 6.

Our paper builds on prior research that finds a positive relation between total plan size and performance. Specifically, Dyck and Pomorski (2011) document that larger plans allocate more to asset classes where their scale is more likely to provide bargaining power with respect to the fees charged by external asset managers, specifically, private equity and real estate. Our analysis generalizes these findings in several ways. First, our empirical analysis focuses on the endogenous choice of plans between internal and external management of their assets, as well as their endogenous choice between active and passive management. Our empirical model allows for separately measuring the probability of a plan to employ internal (or active) management, followed by a measurement of the impact of scale on the level of internal (or active) management—conditional on choosing such mandates. Second, we present results from a matching estimator that allows us to estimate the effect on costs and return performance of plans' choice of internal versus external or active versus passive management, after controlling for plan size and other confounders. Third, we exploit the sub-asset class granularity of our data, and document a power-law relation between size and investment management costs (within a sub-asset class) which more precisely indicates economies of scale in all asset classes, as well as at the plan level, and not just the scale economies in private equity and real estate documented by Dyck and Pomorski (2011). Fourth, we show that economies of scale in costs differ significantly across passive and active mandates, while they are similar for internally and externally managed accounts. Fifth, compared to Dyck and Pomorski (2011), our dataset extends the time series by ten years, enabling us to investigate the time trends in management choices. These trends are critically influenced by the growing scale of DB plans relative to the markets in which they invest, as well as time-series changes in the fixed-costs required to set up internal management.

The remainder of the paper proceeds as follows. Section 2 introduces the main features of our data from CEM with additional details provided in Appendix A. Section 3 develops a set of hypotheses that we set out to test empirically in the subsequent analysis. Section 4 covers the determinants of internal versus external and active versus passive investment management decisions. Section 5 provides a detailed analysis of the cost data, and Section 6 analyzes gross and net-of-cost return performance and how it relates to plan characteristics. Finally, Section 7 analyses how cost and return performance relates to investment management mandates (or "styles") and Section 8 concludes.

2 Data and Summary Statistics

We obtain our data from CEM Benchmarking, a Toronto-based company that uses detailed annual surveys to collect data on public and private pension sponsors domiciled both in the U.S. and in a number of other developed-market countries. A key advantage of this dataset is its highly detailed fee/cost data, separated by sub-asset class, as well as by active vs. passive mandates and by internal vs. external management within each sub-asset class. In total, the CEM Benchmarking database covers 613 U.S. and 524 non-U.S. plans (CEM "PlanIDs") that participated in the survey at some point during our 29-year sample period from 1991 to 2019.[10]

CEM plan surveys in the U.S. and the U.K. are primarily collected from defined benefit (henceforth, DB) pension plans and other similar capital investment pools. Apart from these regions, the type of plans for which the survey is collected is country-specific, such as industry-based DB pools in the Netherlands, buffer funds in Sweden, insurance-backed retirement funds in Finland, or defined contribution plans in Australia. Even though reporting to CEM is voluntary, previous research has found no evidence of self-reporting bias related to performance (Bauer et al., 2010).[11] The self-reported data are checked by CEM for internal (same year) consistency, year-over-year consistency, and outlier reporting. CEM data is biased toward larger plans, yet plans contained in the database are broadly distributed across size (total plan AUM). The aggregate AUM covered by CEM in 2019 is \$9.04 trillion, with U.S. plans accounting for \$3.81 trillion, and non-U.S. plans holding the remaining \$5.23 trillion (using 2019 exchange rates). Some plans only report results for a few years—in some cases only for a single year. However, while roughly 500 plans report to CEM for three or fewer years, 317 plans report to CEM for at least 10 years. This fact, coupled with the large cross-section of plans surveyed by CEM each year (at least since 1999), allows us to analyze a representative sample of worldwide pension plans.[12] Further details on the CEM database, and the mechanism

[10]The CEM dataset has been used in the past by French (2008), who shows that pension plans shift from active to passive management over time, and Andonov et al. (2013), who document scale-economies for pension plan costs in real estate investments. Broeders et al. (2016) looked at scale benefits for Dutch pension plans, using different proprietary data.

[11]From discussions with CEM, the primary reason for funds to leave the survey is turnover in direct contacts with clients, i.e., the personnel of a particular pension plan changes. High-fee plans, predominantly small plans, are less likely to participate in the survey which can be very labor intensive to complete.

[12]Details are provided in Appendix Table D.1. That said, our sample is especially reflective of North American plans. In our empirical results, we point out when differences exist between the early years of our sample and later years—which contain a higher proportion (relative to early years) of plans domiciled

used to collect data from plans, are contained in the Appendix.[13]

The CEM survey collects data on four categories of variables, separately for passively vs. actively managed, and, in turn, for internally vs. externally managed assets within each of six major asset classes (and their corresponding sub-asset classes), namely: stocks, fixed income, hedge funds and multi-asset class (jointly), private equity, private debt, and real assets. Included for each of four potential mandate choices within each asset class (e.g., internal active) is the dollar value of assets (using exchange rates for foreign plans), internal management costs or external management fees (AUM-based as well as performance-related), and asset returns, measured both gross and net of fees.[14] A full list of variables is contained in Appendix B.2—D.

2.1 Asset Allocation

Figure 1 shows the proportion of investments allocated to each of the six major asset classes for U.S. (top panel) and non-U.S. (bottom panel) DB plans. For U.S. plans, the average plan allocation to public equities (stocks) varies between 50 and 60% from the beginning of our sample (1991) until the Global Financial Crisis (2007-2008), after which it drops below 50% of portfolio holdings. These plans increasingly allocate to alternative asset classes by the end of our sample (2019)—from less than 8% in 1991 to almost 28% in 2019. Non-U.S. plans show a similar pattern of asset allocation over time, albeit with lower levels of stock investments.

Even larger shifts have taken place during our sample period in the sub-asset classes that comprise the six main asset classes. Figure 2a shows that the allocation of U.S. plans to broad-based U.S. stock strategies (U.S. Broad/All) is 86% at the beginning of our sample, dropping to 18% by 2019. In turn, these U.S. plans allocated more to international stock strategies, such as ACWI ex U.S., EAFE, emerging markets, and global (12% in 1991 versus 58% in 2019), and allocated more to specialized market capitalization strategies such as small, medium and large cap stocks. Trends in fixed-income investments show a similar movement from broad-based to more specialized mandates. Allocations

outside of North America.

[13]For comparison, according to the Investment Company Institute (2021), in 2019, there were $54.9 trillion of total net assets invested in worldwide regulated open-end funds, with the U.S. accounting for $25.9 trillion, or nearly half, of these investments. The Center for Retirement Research at Boston College (CRR) estimates that U.S. public pension plans held $4.1 trillion of assets in 2019. See https://publicplansdata.org/.

[14]For each asset class, data is subdivided into several sub-asset classes such as U.S. large cap stocks or emerging market stocks, as shown in, for example, Appendix Table D.4.

between alternative sub-asset classes exhibit a trend toward greater allocations to hedge funds (Figure 2c), LBOs (Figure 2d), private credit (Figure 2e), and natural resources and infrastructure (Figure 2f).

Subsequently, we present results for small and large pension plans, defined as plans below the 30th and above the 70th percentile in total plan AUM each year, in Figure 3. This figure includes bar charts for the asset allocation by management mandate within asset classes for the year 2019, with similar results in 1999 and 2009. The three asset classes, stocks, fixed income, and real assets, encompass all four management mandates: internal passive (IP), external passive (EP), internal active (IA), and external active (EA). Passive mandates are not available for the remaining alternative asset classes: private debt, private equity, and hedge funds. Large plans exhibit a higher fraction of internally managed assets, both for active and passive mandates, particularly in publicly-traded fixed income and stocks. These asset classes are associated with the lowest fixed and variable internal management costs, making them more conducive for setting up internal asset management.

Table 1 reports small and large plans' choice of investment management mandate in the form of the share of plans' AUM within individual sub-asset classes allocated to each of the four management mandates (IP, EP, IA, and EA). Large plans make far greater use of internal active management than small plans. This holds both in public asset classes and even more so among the four private asset classes. Differences can be very large, e.g., with 58% of large plans' assets in global equity being managed internally and actively, versus only 1% for small plans. Small plans also make far greater use of external active investment management than large plans.

2.2 Investment Management Cost

We now turn to the time series evolution in investment management cost. We measure the aggregate investment management cost in an asset or sub-asset class as the sum of AUM-based fees and performance-related fees, and report it as a percentage of AUM allocated by a particular DB plan to that asset or sub-asset class during a particular year. Further, we scale the median value of this cost by the "grand average" cost averaged across asset classes, plans and years in our data.[15] This generates a new measure of cost, *scaled cost*, which is expressed as a percentage of the average cost. While this scaling does not show the cost level in bps/year, it allows us to interpret time trends in management cost as

[15] We use this transformation to preserve confidentiality of cost *levels*, as requested by CEM.

well as compare costs across different asset classes and management mandates.[16]

First, consider investment management costs for stock holdings (Figures 4a and 4c). For passively managed accounts (Figure 4a), median costs increase over time from 5% to 8% of average costs when internally managed, yet decline from 18% to 9% when externally managed. Hence, by the end of our sample, the cost of internal and external passive management converge, suggesting that passive management has increasingly become a "commoditized" investment management service. Active equity management costs are far higher, at 22% of average costs for internally managed accounts, and rising from 81% to 110% of average costs for externally managed accounts. In this case, we do not find any evidence of convergence. Part of the reason for this non-convergence appears to be that plans choose to internalize the active management of the least specialized, lower-cost sub-asset classes (e.g., broad cap U.S. stocks) and conversely externalize the high-cost segments (e.g., emerging market stocks and small cap stocks) which require more specialized knowledge to manage actively. Moreover, as we show subsequently, external fund managers generate positive net-of-fee return performance— especially for the largest pension plans in our sample, serving to reduce pressures on their investment managers to reduce active management fees. We find very similar results for fixed income allocations (Figures 4b and 4d).

In summary, passively managed assets have become largely commoditized, resulting in lower costs, especially for large plans that have transitioned to internal management. Smaller plans, although still reliant on external passive management, benefit from lower fees due to economies of scale in this domain. External active management fees have, in general, remained durably higher than internal active management costs, due to an increasing specialization of external active managers and the alpha benefits such specialization brings to pension plans.

3 Empirical Hypotheses

Our paper examines investment management costs and return performance as a function of pension plan scale and plans' choice of investment management style (internal vs. external and active vs. passive). Our primary focus is on understanding how economies of scale affect investment costs, specifically the fixed costs associated with different al-

[16] For example, a *scaled cost* of 100% implies that the median costs are equal to the average costs in our sample while a value of 50% implies a median cost of half the average cost. Appendix Table D.10 reports scaled costs by asset class and country-of-domicile for plans for selected years.

locations, such as those to active or passive management, as well as internal or external management.[17]

That is, a key theme of our paper is the role of fixed costs in investment management and its impact on economies of scale for pension plans. We highlight the bargaining power that large plans gain because of their ability to manage investments internally, potentially avoiding the higher costs associated with external managers. In this section, we formulate testable hypotheses drawing from theories of asset management, considering scale economies, uncertainty in active management skills, the cost of information acquisition, and heterogeneity in investors' abilities to identify skilled managers

3.1 Theories of Asset Management

3.1.1 Berk and Green (2004)

A useful starting point for our inquiry is the seminal paper of Berk and Green (2004) (BG). In mutual fund markets, BG propose an equilibrium model that starts with the assumption of homogeneous diseconomies of scale among funds in their investments in financial markets. Given the implied absence of any differential bargaining power of (atomistic) mutual fund investors in their model, mutual funds, in equilibrium, grow to a size at which their diseconomies result in zero expected net-of-fee alphas.[18]

In our setting that includes some very large pension plans as well as a finite set of small plans, we can expect important deviations from this idealized BG "no-frictions equilibrium" outcome. Specifically, the differential bargaining power of individual plans cannot be dismissed, and brings many interesting features to the competitive market for investment managers who cater to such plans.[19] That is, the industrial organization

[17]Fixed costs include the costs of setting up a management "shop", such as the costs of office space, datasets, and human capital, both for internal and external management—but, also, the search costs of plans in locating skilled active external managers.

[18]That is, open-end mutual fund managers allow their funds to grow to a size that leaves zero expected alphas, net-of-fees, to rational atomistic investors in their funds—but that maximizes fund manager fee income. So, in BG's implied setting of a limited number of truly skilled asset managers, all of the expected rents (ex-ante alphas) accrue to investment managers, since the infinite pool of investors (supply of capital) competes away any net-of-fee performance through their inflows to funds rationally inferred to be overseen by skilled managers.

[19]BG allow for a limited role for the fixed costs of active investment managers, i.e., in modeling the decision of such managers to continue operations or to shut down. In our setting, the fixed-costs of investment management, both active and passive, as well as internal vs. external management, are central to the ongoing choices made by pension plans. This distinction implies that there exist scale economies at the plan level which affect both investment costs and allocations to external vs. internal management, abstracting from the choice of investment managers to discontinue their operations.

of the market for delegated investment management in the pension fund industry is far more complex than that modeled by BG for the mutual fund industry, with outcomes depending on issues such as the relative bargaining power of plans and managers.[20]

For example, the median plan in the CEM database (based on U.S. equity dollar allocations), in 2019, contains U.S. equity investments totalling $1.01 billion, while the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile plans oversee $107.0 million and $9.25 billion, respectively. While U.S.-domiciled equity mutual funds exhibit a similar dispersion in size, most investors in mutual funds have a relatively small investment and can be considered "atomistic"—that is, they have an insufficient ownership fraction to incentivize or to empower them to negotiate fees with their fund managers.[21]

Thus, while net-of-fee scale diseconomies may be relatively homogeneous among mutual fund investors, mostly due to their limited (collective) negotiating power, such diseconomies can be expected to be much more diverse among pension plans. Small plans might be expected to hold little power to negotiate with their investment managers due to their high fixed costs of search and internal management (per unit of AUM), and, accordingly, may face qualitatively similar net-of-fee diseconomies of scale as investors in mutual funds; in contrast, large plans might use their bulk to reduce diseconomies, or to potentially reverse them and to realize positive scale economies in investment management fees.

3.1.2 Gârleanu and Pedersen (2018)

Addressing some of these limitations of the BG model, Gârleanu and Pedersen (2018), henceforth GP, develop a general equilibrium model for assets and asset management in the presence of fixed costs that pose a friction for all investors (in our setting, for DB plans). The GP model introduces delegated investment management with uninformed and informed managers, where the latter receive a signal that is correlated with returns on a risky asset, as in Grossman and Stiglitz (1980). Importantly, the true manager type

[20] Prior papers on pension plan choice of investment managers (and their dismissal) do not focus on the role of plan scale in such manager choice and negotiated fees (see, e.g., Blake et al. (2013), Rossi et al. (2018) and Beath et al. (2022)).

[21] Among U.S.-domiciled domestic equity mutual funds, the median fund manages $514 million, while funds at the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles, respectively, manage $38.7 million and $6.8 billion, respectively, at the end of December 2019. For comparison, the median amount invested in mutual funds by U.S. households was $200,000 in 2021 (Investment Company Institute, 2021). We recognize that fiduciaries of large defined contribution (DC) plans—some of which hold greater than $1 billion in AUM—might hold some bargaining power with their investment managers (see, for example, Sialm et al. (2015)). However, large DC plans hold levels of AUM that tend to pale in comparison with that of large DB plans.

(informed vs. uninformed) is unobserved by investors, and a fixed search cost must be paid to help identify skilled investment managers.[22]

Our pension plan setting shares similarities with GP's deviation from the BG model. Most importantly, we observe wide heterogeneity in asset allocations among pension plans, impacting their capacity and motivation to cover fixed costs associated with external manager search or internal management setup. Large plans with billions of dollars to invest and many experienced professionals can better handle the fixed costs of internal management and are expected to be more capable of identifying skilled managers.[23] Conversely, small plans will neither have the incentive to undertake costly search, nor to establish internal management, leading to distinct choices between external and internal management. Thus, the choice between external and internal management will be indicative of the fixed costs of internal vs. external management, especially among large pension plans. Small plans can be expected to choose the "corner solution" of no internal management.

The model of Gârleanu and Pedersen (2018) can also be used to compare outcomes in private asset markets, such as real estate and private equity, which display high search and information costs, versus more transparent and lower information-cost asset markets for publicly traded securities, such as stocks and bonds. Specifically, in asset markets with lower search costs for locating skilled active managers, as well as lower information acquisition costs for such managers, the increased competition among active managers both reduces the average active "alpha" (before fees), and applies pressure on active managers to reduce fees. In the face of these shrinking fees, we can expect to see more specialization in active management, as we have described in Section 2.2. With these developments, it naturally follows that passive management gains market share among less-specialized investment strategies relative to active management, when search costs are low and information acquisition is less costly.

Conversely, search costs tend to be much higher in the market for managing private assets, as well as less efficient public-market assets, and only investors with the capacity

[22]Investors have the option of either investing their money directly (passively) and, thus, foregoing the search cost, or searching for an informed manager who will charge a fixed investment fee for actively managing investor assets. The size of this fee is modeled through Nash bargaining between the manager and investor. This feature of the GP model suggests that investors' bargaining power should matter to their choice of investment mandate as well as to investment alphas and fees.

[23]To be sure, large plans are more likely to have access to the most skilled managers due to the greater fee income that they potentially bring, which can compound the advantages that their greater manager search capabilities bring. In this paper, we focus on the bargaining power possessed by large plans due to their enhanced ability to "internalize" investment management.

for undertaking a sophisticated search process (i.e., low search costs relative to AUM) might hire active managers in these markets. Information acquisition costs (paid by active investment managers) also tend to be higher in these markets, and prices are less efficient due to the higher cost of entry and the resulting weaker competition among informed managers. To cover their higher information acquisition fixed costs, investment managers also charge higher fees in private asset markets. In equilibrium, we would expect larger pension plans to be more willing to engage with skilled managers in private markets, in part because of their enhanced ability to locate skilled managers as well as the negotiating power that large plans possess. That is, the market for private investments can be expected to be less important for small pension plans, as they are unable to bargain for positive expected risk-adjusted returns.

In turn, informed managers in private asset markets will tend to earn higher fees due to the high fixed-costs of search and internalization by pension plans. Similarly, to compensate investors for the higher cost of searching for managers of private asset classes, we expect to find higher abnormal returns, net of fees in private markets—among those large plans that have bargaining power.

3.2 Plan Size and Choice of Investment Management Style

Based on the discussion of the key factors determining pension plans' choice of investment management mandate, asset allocation decisions, and investment performance as well as costs, we now articulate a set of hypotheses that discipline our subsequent empirical analysis. Our first hypothesis involves plan size and the corresponding choice of investment management mandate (internal vs. external management, and active vs. passive management).

We believe that large plans have much stronger incentives for internal investment management due to the fixed costs of asset management in all asset classes.[24] Consequently, large plans are expected to allocate a higher proportion of assets internally within asset classes where their investments are larger, and the cost advantage of internal management over external management is more pronounced.

A second dimension is the choice of active vs. passive management. In the Gârleanu and Pedersen (2018) model, small investors with high manager search costs typically choose passive investment due to the significant fixed cost of searching for skilled man-

[24] We recognize that fixed costs are likely smaller in some asset classes and strategies than others in our discussion to follow. For example, fixed costs in managing U.S. equities, passively, is likely to be lower than other asset classes/strategies.

agers. Conversely, large investors, with a more favorable cost-benefit profile due to their higher search capacity and assets, are inclined to seek out active managers. This leads to the expectation that small plans would allocate more of their assets passively, while large plans would favor active management. This tendency might be more pronounced in private asset classes, whereas the situation in public asset markets may differ. The combined effect of a smaller scope for generating abnormal returns and larger diseconomies of scale in the highly competitive stock and bond markets may incentivize large plans to make greater use of internal active rather than external active management in order to reduce investment management costs.

As plans grow in size, they tend to explore alternative asset classes as they exhaust opportunities in the crowded public equity and fixed income markets. Plan size also plays a role in the available choices within each asset class. Larger plans can leverage their size to negotiate more favorable terms, including lower fees in alternative asset classes that might be less accessible to smaller plans. Consequently, we anticipate a positive relation between plan size and allocations to private asset classes, while expecting a negative association between plan size and investments in public stocks and bonds. We summarize these relations between investment choices and plan size in the following hypothesis:

Hypothesis I (Plan size and investment management). *Large pension plans, relative to other plans:*

(i) manage a bigger fraction of their assets internally, measured across all asset classes.

(ii) have a higher probability of switching from external active management to internal active management in public asset classes.

(iii) allocate a larger fraction of their portfolios to private asset classes and, correspondingly, a smaller fraction of their portfolios to public assets (stocks, bonds).

3.3 Economies of Scale in Investment Management Costs

Economies of scale matter in investment management because many costs, such as legal, data, and computing expenses, are either fixed or do not increase proportionally with assets under management. This suggests an inverse relation between a plan's holdings in a specific asset class and the average costs of managing it, meaning that larger plans typically experience lower costs and fees per dollar invested compared to smaller plans. Still, larger plans may also face higher costs due to the need for additional personnel and increased transaction expenses when dealing with larger investment amounts. Investment management costs can also vary depending on the labor-intensity of different investments, influenced by factors such as asset class liquidity and transparency.

To better understand scale economies in investment management costs, we examine the power law framework developed by Gabaix (2009, 2016), positing that dollar management costs, $\text{Cost}^{\$}$, follow a power law as a function of AUM:[25]

$$\text{Cost}^{\$} \propto \text{AUM}^{\beta}. \tag{3.1}$$

Power law coefficients $\beta < 1$ are consistent with economies of scale in investment management costs, and the smaller is β, the bigger the cost economies of scale. Conversely, $\beta > 1$ suggests diseconomies of scale since increasing AUM by a certain factor leads to disproportionately higher management costs.

We use the posited relation in (3.1) to formulate a set of hypotheses on economies of scale in investment management. Our most basic hypothesis is that costs grow less than proportionately with assets under management, i.e., $\beta < 1$. Our next cost hypothesis is that investment management costs vary systematically across public and private asset classes. Specifically, we would expect greater cost economies of scale for public asset classes such as stocks and fixed income (β^{public}) that are traded in transparent and liquid markets than for private asset classes ($\beta^{private}$) which typically involve more labor-intensive (less computerized) processes that are harder to scale up.

Scale economies in costs are also likely to be linked to management mandate, so we analyze the cost-size relation at the asset class level for the four different mandates, namely, Internal Passive (IP), Internal Active (IA), External Passive (EP), and External Active (EA).[26] Passive investment management has largely become commoditized in a way that facilitates scaling more easily than the labor intensive active investment management process. Moreover, besides lower per-dollar human-capital costs, large passive management funds can implement trading strategies that enhance their returns, such as securities lending and favorable per-dollar trading terms with prime brokers, relative to smaller passive funds. Hence, our third cost hypothesis is that passive investment management lends itself more easily to scaling than active management, in part because it is

[25]Two variables X and Y are said to be related via a power law if $Y = cX^{\beta}$, where c is an arbitrary constant. Gabaix (2009, 2016) suggests that power laws are ubiquitous among economic variables such as firm or city size, income, and wealth. While these power laws typically hold primarily in the tails of the distribution, we find the assumption plausible across the entire distribution (see Figure 5).

[26]For private assets, we focus on active management mandates only, since the vast majority of such assets are actively managed.

associated with lower market impact.

For both internal and external management to coexist within a specific asset class, and to align with the empirical observation that not all plans exclusively manage their assets either internally or externally, we propose our fourth cost-scale hypothesis. This hypothesis tests whether economies of scale for both management mandates (internal vs. external) are equal, i.e., that there is an equilibrium where pension plans optimally decide whether to use internal or external investment management for a given asset class. Additionally, this equilibrium assumes that identical scaling technologies are applied in both internal and external asset management.

Hypothesis II (Economies of scale in investment management costs)**.** *In the context of the power law relation in (3.1), the following holds:*

(i) Pension plans' investment management costs display significant economies of scale and exhibit a concave relation to AUM: $\beta < 1$*.*

(ii) Economies of scale in the cost of investment management are greater for publicly traded assets than for private asset classes: $\beta^{public} < \beta^{private}$*.*

(iii) For each asset class, and for both internally and externally managed accounts, passive investment management offers better economies of scale than active management: $\beta^{IP} \leq \beta^{IA}$ *and* $\beta^{EP} \leq \beta^{EA}$*.*

(iv) For each asset class and management mandate (active or passive), the economies of scale cost parameter is identical for internally and externally managed assets: $\beta^{IP} = \beta^{EP}$*, and* $\beta^{IA} = \beta^{EA}$*.*

3.4 Plan Size and Return Performance

Our final set of hypotheses is concerned with how return performance, both gross and net of fees, varies across plan size, investment mandate, and asset class. Plan size can have both a positive and a negative impact on investment performance. In particular, large plans have more resources to search for skilled managers and monitor their return performance on a continual basis, allowing them to better reduce the challenge of plan scale in generating higher gross returns (before fees). Conversely, AUM can have a negative effect on gross returns as managers with more money to invest run out of ideas. Importantly, though, this mechanism is most relevant for externally managed assets.

Plan size will further impact investment performance net of fees positively if there are sizeable economies of scale in the cost of investment management. That is, the existence of significant fixed costs in asset management gives large plans a distinct advantage, especially in active management and in private asset classes. Large plans can also be assumed to possess more bargaining power which they can use to negotiate more favorable terms with external managers. Moreover, because large plans are more likely to have internal asset management capabilities, they can use this as a credible "threat" or reservation point in negotiations with external managers.

Asset classes matter to this relation because of the large differences in acquiring information and managing investments in public and private asset classes and even within these broad categories. Information costs are generally much higher for private assets such as real estate, private equity, and venture capital. Competition among managers of private assets is also not as fierce as that for public asset classes such as stocks and fixed income which offer passive investment products that help bound how high investment management fees can go.

Hypothesis III (Plan size and return performance)**.**

(i) The largest plans earn positive investment returns both before and after fees, i.e., gross and net return performance is an increasing function of plan size.

(ii) Net-of-fee returns are particularly strongly positively related to plan size for private asset classes.

We next set out to test these hypotheses more formally, beginning with plans' choice of investment management styles (Section 4), moving on to investment management costs (Section 5), and finishing with return performance (Section 6).

4 Investment Management Mandates

This section examines the impact of plan, manager, and asset characteristics, including plan size (AUM), investment management costs, and plan domicile, on the choice of investment management mandate. Specifically, it assesses whether plans opt for internal or external asset management, and whether they favor active or passive investment management. Our analysis performs a set of regressions that use as dependent variable the proportion of investments in asset class A, in a given year, t, that is managed by plan i in a certain strategy, denoted ω_{iAt} and defined in more detail below. For example, ω_{iAt} can denote the proportion of investments in asset class A that are managed internally. We regress this proportion on a set of covariates, x_{iAt}, as well as asset-class and time fixed effects, c_A and λ_{At}:

$$\omega_{iAt} = c_A + \lambda_{At} + \beta_A' x_{iAt} + \epsilon_{iAt}. \tag{4.1}$$

In practice, internal management involves substantial fixed-cost investments, including hiring compliance staff and traders, IT system setup, database subscriptions, and hiring skilled investment analysts. Many plans, especially smaller ones, allocate zero assets to internal management due to these fixed costs. Similarly, it is uncommon for plans or external managers to manage alternative asset classes passively. The panel regression in (4.1) does not account for the presence of many "zeros" in the data. It focuses on estimating plan choices between management mandates (internal vs. external or passive vs. active) at the intensive margin. However, this approach may introduce model misspecification because variables like plan size and management costs likely influence both the *extent* to which a plan manages assets internally and whether it chooses internal management for *any* of its assets.

To deal with the large number of zeros and to obtain an estimate that accounts for plans' choice along both the intensive and extensive margins, we use the Cragg (1971) estimator. This estimator consists of two equations, namely (i) a selection equation that estimates the probability that a plan's allocation choice lies on the boundary (e.g., zero internal management); and (ii) an outcome equation that estimates the effect of a variable on the proportion of assets managed internally for plans with at least some internal management in that asset class. More formally, the regression model we estimate takes the form:

$$\omega_{iAt} = s_{iAt} h^*_{iAt},$$

$$s_{iAt} = 1\left[\gamma' x_{s,iAt} + \varepsilon_{iAt} > 0\right], \tag{4.2a}$$

$$h^*_{iAt} = \exp\left(\lambda_{At} + \beta' x_{o,iAt} + e_{iAt}\right), \tag{4.2b}$$

where s_{iAt} is a selection indicator that depends on $x_{s,iAt}$ (covariates influencing selection) and h^*_{iAt} denotes the choice or outcome variable that depends on $x_{o,iAt}$. If the selection indicator equals zero, the dependent variable ω_{iAt} will also take a value of zero and, hence, lie on the boundary.[27]

[27] This model is more flexible than a standard Tobin (1958) model, since the variables determining

Assuming that the error terms ε_{iAt} and e_{iAt} in (4.2a) and (4.2b) are independent normal random variables with marginal distributions $\varepsilon_{iAt} \sim N(0,1)$ and $e_{iAt}|x_{o,iAt} \sim N(0,\sigma^2)$, the conditional expectation of ω_{iAt} given the variables $x_{s,iAt}, x_{o,iAt}$ simplifies to

$$\mathbb{E}\left(\omega_{iAt}|x_{s,iAt}, x_{o,iAt}\right) = \Phi\left(\gamma' x_{s,iAt}\right) \exp\left(\lambda_{At} + \beta' x_{o,iAt} + \frac{\sigma^2}{2}\right), \tag{4.3}$$

where $\Phi(\cdot)$ is the CDF of the standard normal distribution.

To gauge the effect of changing a single variable, x, on the expected value of ω_{iAt}, we examine the average partial effect (APE) of x:

$$\text{APE}_x(x_{s,iAt}, x_{o,iAt}; \gamma, \beta) = \left.\frac{\partial \mathbb{E}\left(\omega|x_s, x_o\right)}{\partial x}\right|_{x_s = x_{s,iAt}, x_o = x_{o,iAt}}. \tag{4.4}$$

Since the expectation in (4.3) depends on both the selection and outcome equations, the APE in (4.4) accounts for both the intensive and extensive margin effects of changing x and so depends on both γ and β. Letting $\widehat{\gamma}$ and $\widehat{\beta}$ denote the maximum likelihood estimates, we can compute the sample APE as

$$\widehat{\text{APE}}_x = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \text{APE}_x(x_{s,iAt}, x_{o,iAt}; \widehat{\gamma}, \widehat{\beta}). \tag{4.5}$$

Intuitively, $\widehat{\text{APE}}_x$ captures the average effect of changing x while holding all other variables constant.

4.1 Internal versus External Management

To examine the determinants of plans' decision on managing investments in a given asset class internally or externally, we estimate models for the proportion of plan i's allocation to asset class A that is internally managed in year t, $\omega_{iAt}^{internal} := \text{AUM}_{iAt}^{internal}/\text{AUM}_{iAt}$, where $\text{AUM}_{iAt}^{internal}$ and AUM_{iAt} refer to the internally managed and total AUM of plan i in asset class A of year t.

We consider the following variables. First, to capture plan size, we include $\log(\text{AUM}_{it-1})$, the logarithm of the total dollar value of plan i's assets under management (AUM) in year

selection (extensive margin) can be different from the variables driving the outcome (intensive margin) equation. Moreover, since γ and β are decoupled, the effect of a variable on the selection and outcome equations can also be different.

$t-1$.[28] Second, we include the lagged spread in the cost of external versus internal management in asset class A measured in basis points ($\text{CostSpread}_{iAt-1}^{E-I}$). Third, we include a dummy that takes a value of one for non-U.S. plans and is zero otherwise (nonUS_i) and a dummy that takes a value of one for private plans and is zero otherwise (Private_i). Finally, we include asset class fixed effects, c_A, and year fixed effects, λ_{At}, leading to the model:

$$\begin{aligned}\omega_{iAt}^{internal} = c_A + \lambda_{At} + \beta_{1,A}\log(\text{AUM})_{it-1} \\ + \beta_{2,A}\text{CostSpread}_{iAt-1}^{E-I} + \beta_{3,A}\text{Private}_i + \beta_{4,A}\text{nonUS}_i + \epsilon_{iAt}.\end{aligned} \tag{4.6}$$

Table 2 reports our regression results. To retain a parsimonious specification for the Cragg estimator, we include only the log-size and cost spread between external and internal in the selection equation (4.2a) whereas in the outcome equation (4.2b) we further include time fixed effects and the dummies for whether a plan is private or public and domiciled inside or outside the U.S. Our estimates of average partial effects are shown in columns to the right of the panel estimates in the table.

Across all asset classes, our estimates show that larger plans employ internal management to a significantly greater extent than smaller plans, consistent with Hypothesis I(i). For instance, our panel estimates in Panel A of Table 2 indicate that a 10% increase in plan size is associated with roughly a one percent increase in the proportion of the plan's stock portfolio that is managed internally (0.83% and 1.14% for the panel and Cragg estimates, respectively). A 10% increase in plan size is associated with a comparable but slightly bigger increase in the proportion of the plan's fixed income portfolio that is internally managed (1.10% and 1.77%).

For alternative asset classes we continue to see a significant association between plan size and the proportion of those asset classes that is managed internally, but the effects are generally not as strong as for stocks or fixed income, with the exception of private debt.

Our Cragg estimates on log-size are notably larger than the corresponding panel estimates for both stocks and fixed income. This finding can be attributed to the fact that plan size increases both the proportion of assets managed internally for plans already using internal investment management and the likelihood of plans transitioning from *no* internal management to *some* internal management. This highlights the importance of explicitly accounting for selection effects.

[28] Plan AUM is typically measured at the end of the year.

Panel B in Table 2 verifies this point by reporting estimates from the Cragg selection regression. The table quantifies the effect of lagged AUM and the cost spread on the probability that plans manage at least some of their investments in a given class internally. The first row of estimates shows that plan AUM in a given asset class is a highly significant determinant of the probability that a plan manages some of its assets internally within the asset class. All coefficient estimates on log-size are positive, so larger plans are significantly more likely to manage some of their assets internally, regardless of asset class. In contrast, the external-minus-internal cost spread appears to be a far less important determinant of plans' decision on whether to employ internal asset management and this variable is only statistically significant for one asset class (Hedge funds and multi assets).

The lower panel in Table 2 illustrates the importance of these estimates by reporting the probability that a plan manages some of its assets internally as we vary the plan size from the 10th through the 50th and 90th percentiles of the 2019 AUM distribution. We keep the cost spread at its average value in these calculations, although this is not important given that the cost spread does not have a big effect on the results. For stock holdings, we find that small plans (in the 10th percentile of the AUM distribution) have a 13% chance of managing some of their stock portfolio internally. This rises to 34% for medium-sized plans and to nearly 66% for plans in the 90th percentile of the size distribution. Hence, large plans are five times more likely to manage some of their stock holdings internally than small plans. Similarly, large plans are almost three times more likely to manage some of their fixed income holdings internally than small plans (72% versus 29%).

Small plans rarely manage private assets internally, except for real assets (12.82%). Specifically, the Cragg probability estimates vary from 0.50% to 9% for plans located at the 10th percentile of the size distribution. These probability estimates rise notably to between one-tenth (10.59% for hedge funds) to one-half (52.56% for private debt) for the largest plans, i.e., those in the 90th percentile of the size distribution.

These estimates are all consistent with Hypothesis I(i). Moreover, our estimates are also consistent with relatively modest fixed costs of setting up internal management shops in stocks and bonds, as compared to doing so for alternative asset classes (such as private equity) that require more specialized skills and knowledge, as well as more costly connections to external sources of information. Consequently, it is rare for small plans to manage their alternative assets internally.

To summarize, our findings suggest that plans' decision to overcome the hurdle of managing at least some of their investments in a given asset class internally is mainly determined by plan size, whereas the cost spread (external versus internal) is not as important (of course, interpreted with caution due to the endogeneity of internal management as a function of costs). Conversely, for plans that have decided to manage some of their assets internally, the cost spread is important for how large a proportion of their assets they manage internally.[29]

We now turn to the estimation of average partial effects. Equation (4.3) shows that the average partial effect is a nonlinear function of the covariates. The effect of changing plan size or the cost spread therefore depends on the initial value from which the variable is changed. Specifically, consider the APE when a specific covariate, x_{iAt}, takes on the value ξ:

$$\widehat{\text{APE}}_x(\xi) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\text{APE}_x(\widetilde{x}_{s,iAt}, \widetilde{x}_{o,iAt}; \widehat{\gamma}, \widehat{\beta}), \tag{4.7}$$

where $\widetilde{x}_{o,iAt} = [x_{o,iAt} \backslash x_{iAt}, \xi]$ is the vector of variables in the outcome equation with $x_{iAt} = \xi$ and $\widetilde{x}_{s,iAt}$ is defined similarly. For example, (4.7) can used to calculate the APE when $\log(\text{AUM})_{it-1}$ is set at its 10th percentile. To examine if nonlinearities are economically important, we evaluate partial effects at the 10th and 90th percentiles and test if the difference between the two estimates is statistically significant.

Results from this analysis applied to the size and cost spread variables are presented in Panel A of Table 3. For the size variable, the APE is larger by an order of magnitude for the largest plans (90th percentile) than for the smaller ones (10th percentile). For example, going from a plan with a small stock portfolio (10th percentile) to a plan with a large stock portfolio (90th percentile), our estimates suggest that the two plans will increase the proportion of their internally managed stocks by 0.38% and 3.19%, respectively. Moreover, these differences are statistically significant for the public asset classes, and positive for all private asset classes. Hence, big plans are disproportionately more likely to move public assets from external to internal management as they grow larger.

For the cost spread, plans that pay the highest costs (90th percentile) for management of their fixed income assets are significantly more likely to move assets from external to

[29] For stocks, as the cost spread increases by 100 bps, the allocation to internal management is predicted to increase by 12.2% (15.3%) based on the Cragg (panel) estimates. For fixed income this effect is bigger at 30.3% (23.8%). The estimated coefficients on the cost spread have the wrong sign and fail to be significant for private equity and private debt. Conversely, the effect is positive for hedge funds and real assets, but insignificant. However, the choice of internal management is endogenous to cost differences, and the composition of externally managed assets can change when internal management is employed, thus making a clean interpretation of the cost spread coefficient difficult.

internal management than the plans that pay the lowest costs (10th percentile). This makes good sense since the low-cost group has a weaker incentive to switch from external to internal management as they already pay relatively low costs. For the other asset classes, the APE of the cost differential fails to be significant.

4.2 Active versus Passive Management

We next use our framework to examine the determinants of plans' decisions to use active or passive management in different asset classes. Let $\omega_{iAt}^{active} := \text{AUM}_{iAt}^{active}/\text{AUM}_{iAt}$ be the fraction of investments in asset class A that is actively managed by plan i in year t. We use this as our dependent variable in a set of panel regressions

$$\begin{aligned}\omega_{iAt}^{active} &= c_A + \lambda_{At} + \beta_{1,A}\log(\text{AUM})_{it-1} \\ &\quad + \beta_{2,A}\text{CostSpread}_{iAt-1}^{A-P} + \beta_{3,A}\text{Private}_i + \beta_{4,A}\text{NonUS}_i + \epsilon_{iAt},\end{aligned} \tag{4.8}$$

with all variables previously defined, except $\text{CostSpread}_{iAt-1}^{A-P}$, which denotes the basis point spread between the cost of active and passive management for plan i in asset class A at time $t-1$. Because the vast majority of plans do not use passive management in alternative asset classes, we only have sufficient data to report estimates for stocks, fixed income and real assets.

Table 4 reports estimates from the panel regressions in (4.8) as well as for the Cragg estimator using the same format as in the previous subsection. For stock portfolios, we find that larger plans manage a significantly higher proportion of their stock holdings passively, as both the panel and Cragg estimates of the coefficients on log-size are negative and statistically significant. For every 10% increase in plan size, the proportion of stock holdings managed passively increases by about 0.4%. Also, a higher spread in the cost of managing stocks actively rather than passively is associated with a large and highly significant negative effect on the proportion of stock holdings managed actively. Specifically, the Cragg estimate suggests that raising this cost spread by 100 bps is associated with a 33% increase in the proportion of plans' stock holdings that are passively managed. Private plans also manage significantly more of their stock portfolios actively than public plans do.

For fixed income holdings, we find some evidence that larger plans manage a slightly higher proportion of their assets actively, as the Cragg APE estimate of log-size is significantly positive. However, the effect is small and the panel estimate is insignificant.

The Cragg APE estimate on the cost spread is highly significant and negative, suggesting that higher active management costs, measured relative to passive management costs, lead plans to significantly increase the proportion of their passively managed fixed income holdings.[30]

Plans can mitigate the higher costs of active investment by transitioning from external active management to internal active management, which is typically more cost-effective. This strategy is likely to be particularly appealing for the largest plans with the greatest capacity for overcoming the fixed costs of setting up internal management. To explore if this holds in our data, we examine the proportion of plans' actively managed stock and bond portfolios that are managed internally in the right panel of Table 4.

For both stock and fixed income holdings, we find that the estimated coefficient on log-size is positive and highly significant. Hence, an increase in plan AUM is associated with a significantly higher allocation to that part of plans' actively managed portfolios that is managed internally, consistent with Hypothesis I(ii). A higher spread in the costs of active versus passive management also leads to plans internalizing more of their actively managed stock and fixed income portfolios.

Table 4 also reports estimates on dummies for whether a plan is private or public and whether a plan resides in the U.S. or outside the U.S.. Our Cragg estimates show that private plans tend to allocate approximately 4.8% more of their stock holdings to active management than their public peers while we find no significant difference between U.S. and non-U.S. plans. For fixed income holdings, we find that non-U.S. plans manage 9.8% less of their fixed income holdings actively than U.S. plans.

While many plans mix different management mandates at the asset class level (e.g., external active and external passive management of their stock portfolio), they mostly choose a single management mandate at the sub-asset class level. In other words, it is common to find asset managers that employ internal passive management for their U.S. Large cap portfolio and external active management for their emerging market stock portfolios, but it is rare to see managers that simultaneously employ different management mandates for their U.S. large cap portfolio. In those cases where plans mix multiple management mandates for a particular sub-asset class, this tends to be done exclusively by the largest plans.

Finally, we consider again the APE estimates evaluated at different percentiles of the

[30]For real assets, we find a negative relation between plan size (AUM) and the proportion of actively managed assets, but the estimated effect is small and insignificant. This finding reflects that very few plans in our dataset manage real assets passively and, for those that do, predominantly in one sub-asset class, namely REITs.

size and cost spread distribution. Our estimates are presented in Panel B of Table 3. Most of the differences in APE estimates are statistically insignificant. Plans paying the highest costs for active equity management (90th percentile) are more likely to move their stock holdings from active to passive management than are plans paying the lowest costs (10th percentile)—a point that is driven by externally managed holdings. Interestingly, the rightmost column in the table shows that, for fixed income investments, the largest plans (90th percentile) are considerably more likely than smaller plans (10th percentile) to switch from external active management to internal active management as they grow larger.

4.3 Asset Allocation Decisions

To examine if plans' asset allocation decisions are consistent with Hypothesis I(iii), we conduct a set of panel regressions that use as dependent variable the weight of asset class A for plan i in year t, $\omega_{iAt} = \text{AUM}_{iAt}/\text{AUM}_{it}$, which we model by:

$$\begin{aligned}\omega_{iAt} = c_A + \lambda_{At} + \beta_{1,A}\log(\text{AUM}_{it-1}) + \beta_{2,A}\text{Cost}_{iAt-1} \\ + \beta_{3,A}\text{Private}_i + \beta_{4,A}\text{nonUS}_i + \beta_{5,A}\text{LiabilityRetiree}_{it} + \epsilon_{iAt}.\end{aligned} \tag{4.9}$$

The list of regressors is similar to that adopted earlier with two exceptions. First, our cost variable (Cost_{iAt-1}) is now the lagged per-dollar cost for plan i in asset class A measured as a fraction of AUM and denoted in bps. Second, we also control for liability-related effects on asset allocation decisions by including $\text{LiabilityRetiree}_{it}$, the fraction of a plan's total liabilities owed to retirees. We do so because plans are likely to consider their liability structure when deciding how much to allocate to asset classes with different risk characteristics. For example, more mature plans may allocate a larger fraction of their portfolio to fixed income. Because only a subset of plans report data on liabilities, including this as a covariate results in a substantial decline in sample size. We therefore report in Table 5 results both with (Panel B) and without (Panel A) this variable included.

We find evidence largely consistent with our empirical prediction as larger plans allocate significantly less of their portfolios to stocks, fixed income, hedge funds, and private debt. Conversely, they allocate a significantly greater share of their investments toward private equity and real assets. These findings hold regardless of whether we estimate our panel regressions on the larger sample (top panel), or on the smaller sample that controls for plan liabilities (bottom panel).[31]

[31] Our estimates are consistent with the findings reported in Dyck and Pomorski (2011).

Investment management costs are also an important driver of plans' asset allocation decisions. We obtain negative and highly significant estimates on the cost variable for five of the six asset classes with the sixth (private debt) being insignificant. Coefficient estimates vary greatly across asset classes; by far the highest estimate is obtained for fixed income (-20.10) and stocks (-7.11) with smaller estimates for hedge funds and multi assets (-1.65) and, in particular, real assets (-0.44) and private equity (-0.11). In contrast, the estimates of the LiabilityRetiree variable in the bottom panel of Table 5 are statistically insignificant across all asset class specifications, except for stock investments.

5 Investment Management Costs

Our above results indicate that plan size plays an important role in determining the choice of investment management mandate. In concert with these choices, plan size is likely to be a key determinant of investment management fees/costs, as larger plans benefit from internal management scale economies and possess greater bargaining power to negotiate external management fees. This section explores the role of plan size in determining investment management costs across different asset classes and investment management mandates. Our focus is on how larger plans can use the threat of internal management to establish bargaining power with external managers, particularly in asset classes with relatively low fixed costs of setting up such management.

Taking logs in the power law equation in (3.1), we obtain a linear relation between the log-cost and log-AUM whose slope measures the economies of scale coefficient, β. To see if this is a suitable characterization of the cost-size relation in our data, Figure 5 provides log-log plots of AUM versus costs for stocks and fixed income portfolios across the four investment management mandates. These plots suggest that the power law provides a good approximation to the cost-size relation. The slope is notably flatter for passively managed portfolios than for active ones consistent with larger economies of scale (lower β) for passive than for active management of both stock and fixed income accounts.

Generalizing the power law relation in (3.1) to allow for additional determinants of costs, we examine the following model[32]

$$\text{Cost}^{\$}_{iats} = (\text{AUM}_{iats})^{\beta_{As}} \exp\left(c_{As} + \lambda_{Ats} + \gamma_{1,As}\text{Private}_i + \gamma_{2,As}\text{nonUS}_i\right) \exp(\varepsilon_{iats}), \quad (5.1)$$

[32] Bikker (2017) uses different cost functions to show that average costs are decreasing in size and that investment costs are U-shaped. Related to this, Alserda et al. (2018) find large economies of scale for administrative costs, and diseconomies of scale for investment costs.

where $\text{Cost}^{\$}_{iats}$ (AUM_{iats}) is the dollar cost (AUM) of plan i in sub-asset class a at time t for mandate s, c_{As} is a constant that varies across asset classes A and mandate s, λ_{Ats} is a time fixed effect for asset class A and mandate s, Private_i is a dummy equal to one if plan i is private and nonUS_i is a dummy equal to one if plan i is domiciled outside the U.S. Taking logs in (5.1), we obtain the following panel model which allows us to estimate the power law coefficient, β_{As}:[33]

$$\log(\text{Cost}^{\$}_{iats}) = c_{As} + \lambda_{Ats} + \beta_{As}\log(\text{AUM}_{iats}) + \gamma_{1,As}\text{Private}_i + \gamma_{2,As}\text{nonUS}_i + \varepsilon_{iats}. \quad (5.2)$$

We estimate this model at the sub-asset class level to leverage the granularity of the data provided by CEM, significantly increasing the sample size compared to simply using less-granular asset class level data. Notice, also, that we impose homogeneity in the power-law coefficient within each asset class (across its sub-asset classes) so that information from all sub-asset classes is used to estimate the economies of scale parameter for the associated asset class.

The top panel in Table 6 shows estimates of (5.2) obtained for the different management mandates at the asset class level. First, consider the two public asset classes, stocks and fixed income, for which we have sufficient data to consider all four management mandates. Across both asset classes and for all four management mandates, our estimates of β are less than unity and, consistent with Hypothesis II(i), we reject the null hypothesis of no economies of scale, $\beta_{1,As} = 1$.

Turning to the importance of investment mandate for scale economies, our estimates of β_{As} are around 0.75 for passively managed stocks and fixed income assets but closer to 0.90 for actively managed accounts in these asset classes. This suggests that economies of scale are much higher for passively managed than for actively managed public assets. This result seems intuitive, since it is much easier to scale-up an index investment than an active strategy (consistent with the conjecture of Berk and Green (2004)). Our finding that passive management lends itself better to scaling than active management is also consistent with Hypothesis II(iii) and seems highly plausible.[34] Our estimates of

[33]We include time fixed effects but not plan fixed effects in (5.2). Because AUM varies a lot across plans and is highly persistent, including plan fixed effects would make it difficult to estimate the size-cost relationship. For example, a high-profile pension plan with hundreds of billions of dollars in AUM is likely to face very different investment costs compared to a much smaller plan with a few hundred million dollars in AUM and plan fixed effects are likely to capture this.

[34]Passive investment management relies heavily on computer algorithms that are easy to scale up. Passive portfolios may venture into more sub-asset classes as they grow in size in order to limit any adverse market impact, but this is unlikely to raise costs by much. Conversely, active investment management is more labor intensive, and more adversely affected by the market impact of trading and, thus, more

the power law coefficients are very similar within active or within passive management, regardless of whether assets are managed internally or externally. The choice of passive versus active management is thus more important to economies of scale than is the decision for whether to manage assets internally or externally.

Turning to the four alternative asset classes, passive management is uncommon, so we only report estimates for internal active and external active mandates.[35] Table 6 shows that the estimates of β are generally higher than those obtained for stocks and fixed income, averaging 0.95 and ranging from 0.91 to 1.01. This finding is consistent with Hypothesis II(ii), suggesting somewhat *lower* scale advantages in unit investment costs for alternative asset classes, compared with publicly traded assets.[36]

We next consider, in columns two and three of Table 6, investment management cost differences between private vs. public and U.S. vs. non-U.S. plans, respectively. There is evidence that private plans incur higher costs than public plans in the internal and external management of stocks and fixed income assets. We find very little evidence of notable differences in private and public plans' costs of passively managing stocks or fixed-income, as well as managing alternative assets, either internally or externally. Non-U.S. plans pay significantly higher costs, on average, than U.S. plans for both internal and external passive management of stocks and fixed income assets, but pay lower fees for management of these asset classes in external active accounts. Among the alternative asset classes, non-U.S. plans pay significantly higher fees for internal active management of private debt and real assets but they incur significantly lower costs for external active management of private debt as compared to their U.S. peers.

To formally test Hypothesis II that there are statistically significant differences in scale economies between internal/external and passive/active management, respectively, we estimate a model that pools observations across the four management mandates s:

difficult to scale up.

[35]For hedge funds and multi assets, there are only 140 observations of internal active management, so we do not report IA estimates for this case.

[36]This finding is consistent with the far more labor-intensive process of managing specialized asset classes such as private equity. For these asset classes, there is generally no reliable public price that aggregates market information in the same way as for stocks and fixed income, making scaling more difficult and passive management infeasible. The main exception is REITS within the real asset class, but again we do not have a sufficient number of data points on this sub-asset class to conduct a meaningful analysis.

$$\log(\text{Cost}^{\$}_{iats}) = c_{As} + \lambda_{Ats} + \beta_{1,As}\text{Dummy}_s + \beta_{2,As}\log(\text{AUM}_{iats}) + \beta_{3,As}\text{Dummy}_s \times \log(\text{AUM}_{iats}) + \beta_{4,As}\text{Private}_i + \beta_{5,As}\text{nonUS}_i + \varepsilon_{iats}, \tag{5.3}$$

where each of the dummy variables Dummy_s equals one if $s \in \{\text{IA, EA, EP}\}$. The fourth investment management mandate (IP) is treated as the benchmark so all effects are measured relative to this case. For example, for internally managed assets $\text{Dummy}_s = 1$ if $s = \text{IA}$ and zero otherwise so this dummy allows us to estimate the differential impact of internal active management on cost relative to the benchmark of internal passive management. We can test the null hypothesis of no scale differences between internal passive and internal active management by examining the significance of $\beta_{3,As}$.

We present the results of these tests in the bottom three rows of Table 6. For stocks and fixed income, we cannot reject the null hypothesis of equal returns to scale for internal and external passive management, in line with Hypothesis II(iv). Moreover, we cannot reject the null hypothesis that cost economies of scale are identical across internal and and external active mandates for three of five asset classes, the two exceptions being fixed income and real assets. For fixed income assets, internal active management is associated with significantly higher scale economies than external active management ($\beta^{\text{IA}} = 0.84$ versus $\beta^{\text{EA}} = 0.94$), while for real assets internal active management has weaker scale economies than external asset management ($\beta^{\text{IA}} = 1.01$ versus $\beta^{\text{EA}} = 0.92$). Hence the empirical evidence is mixed in relation to Hypothesis II(iv).

Finally, in the bottom row we report p-values for a one-sided test of equal economies of scale in passive and active management for stock and fixed income portfolios against the alternative that cost economies are bigger for passively managed than for actively managed accounts. Consistent with Hypothesis II(iii) we reject the null hypothesis for both stocks and fixed income, which indicates that larger plans, in particular, can achieve significant cost economies by switching from active to passive management.

In summary, our results demonstrate that scale economies in asset management costs vary along two important margins: (i) management mandate (IP, EP, IA, EA); and (ii) asset class. To help quantify the economic importance of variation in costs along these margins, the right panel of Table 6 reports management costs for small, medium, and large plans, represented by the 10^{th}, 50^{th}, and 90^{th} percentiles of the (2019) AUM distribution for a given mandate and asset class combination. These columns summarize the economic effect on costs of the full set of coefficient estimates from our analysis.

Several important points emerge. First, internal passive management leads to substantial cost savings for both stocks and fixed income investments, with external passive management being roughly twice as costly as internal passive management. Second, internal active management costs are lower than external active management costs by an order of magnitude both for publicly traded assets (stocks and fixed income) and also for private asset classes, especially private equity.

Third, there are particularly strong economies of scale across stocks and fixed income accounts, as demonstrated by the significantly lower per-dollar unit cost of plans in the 90th percentile, compared with plans in the 10th percentile of the size distribution. Economies of scale are generally far smaller for actively managed private asset classes, regardless of whether these are managed internally or externally.

We also estimate (5.2) separately for each *sub-asset class*, using only those sub-asset classes that contain a sufficiently large number of observations to allow us to obtain accurate estimates. In Appendix Table D.9, we find that the cost economy of scale estimates are in line with those obtained for the broader asset classes. Economies of scale are notably larger (i.e., β estimates are lower) for passive management of EAFE and U.S. broad stock mandates, as well as for inflation-indexed bonds. In turn, scale economies are much lower for diversified private equity, real estate, and REIT accounts.

6 Investment Performance and Plan Size

Next, we examine how plan characteristics, such as plan size, affects investment performance. As we have seen, plan size is a key determinant of costs. In this section, we explore whether plan size also influences the ability of plans to identify the best-performing asset managers and their bargaining power for net return performance after costs – a crucial question for plan beneficiaries.

A unique feature of our data is that it contains "policy returns" for each plan/sub-asset class/mandate (e.g., an internal active mandate) combination. Policy returns are negotiated targets between fund managers and plan sponsors, and can be used as a simple form of risk-adjustment.[37] Specifically, let r_{iat} be the return of plan i in sub-asset class a during year t, while r^P_{iat} is the associated policy return for the same plan, sub-asset class, and time period. The policy-adjusted return, $\widetilde{r}_{iat}$, is then[38]

[37]This simple, but powerful method for risk-adjusting is especially important for our sample, where many plans are represented for only one or a few years. In subsection 6.2, we explore robustness of our results to using a more conventional risk-adjustment approach based on plans' exposure to a set of common risk factors.

[38]Appendix D reports summary statistics for raw returns and policy-adjusted returns.

$$\widetilde{r}_{iat} = r_{iat} - r^P_{iat}. \tag{6.1}$$

6.1 Return Regressions

We examine the relation between plan characteristics and investment performance through a set of panel regressions that use policy-adjusted returns as the dependent variable. These regressions are estimated separately for each of our asset classes using plan-year sub-asset class returns as the unit of observation, and thus take the form:

$$\begin{aligned}\widetilde{r}_{iat} = c_a + \lambda_{At} + \beta_{1,A}\log(\text{AUM}_{iat-1}) \\ + \beta_{2,A}\text{Private}_i + \beta_{3,A}\text{nonUS}_i + \beta'_{4,A}x_{iat} + \epsilon_{iat},\end{aligned} \tag{6.2}$$

where $\widetilde{r}_{iat}$ denotes the policy-adjusted gross or net return on plan i's holdings in sub-asset class $a \in A$ in year t, c_a denotes a sub-asset class fixed effect, and λ_{At} is an asset-class time fixed effect.[39] Although we use returns at the sub-asset class level, we impose that the coefficient estimates, β_A, are the same within a particular asset class, A. x_{iat} contains a set of control variables that include $\omega^{\text{External}}_{iat}$ (the share of external management), $\omega^{\text{Active}}_{iat}$ (the share of active management), and a dummy equal to one if plan i pays a performance fee at time t in sub-asset class a (Perform_{iat}). To not confound the impact of plan size with the choice of external and active management on returns, we include the latter as controls. Then, in Section 7, we use a matching approach to rigorously estimate the effect of external and active management on returns.

Panel A in Table 7 presents our estimates from regression (6.2), applied separately to gross returns (top) and net returns (bottom). This allows us to examine whether differences in investment performance are explained by differences across plans in costs and fees, as well as differences in pre-fee alphas.

First, consider the relation between plan size and return performance for the two public asset classes. Large plans generate significantly higher policy-adjusted gross returns for stocks than small plans, and this effect is more pronounced for net returns, consistent with Hypothesis III. Specifically, going from a plan ranked in the 10th percentile to a plan ranked in the 90th percentile of the AUM of 2019 plan stock holdings increases the expected policy-adjusted gross and net returns by 26 and 41 bps/year, respectively (see top of Panel B). This is consistent with larger plans exploiting their ability to identify

[39] λ_{At} can help absorb omitted risk factors provided that plan exposures to such factors are relatively homogeneous.

skilled managers and their bargaining power to retain some of the alpha, as implied by Hypothesis III(i).

The size-return relation is stronger among alternative asset classes, particularly for private equity investments. Moreover, the coefficients on size are bigger for net returns than for gross returns, consistent with large plans not only earning higher gross returns in these asset classes than smaller plans, but also paying lower management costs. Differences in the net return performance of large and small plans are economically large. Specifically, going from a plan in the 10th percentile of the 2019 AUM asset class distribution to a plan in the 90th percentile is associated with increases in mean net policy-adjusted returns of 109 bps/year (hedge funds and multi asset), 419 bps (private equity), 79 bps (private debt), and 122 bps (real assets).[40] As a robustness check, we also compute the increase in policy-adjusted gross and net return based on portfolio sorts. In particular, we form equally-weighted portfolio returns based on the bottom 30th and upper 70th size percentile within each year.[41] We then calculate the time series average return for portfolios sorted on size. The bottom rows of panel B in Table 7 show that the size effect is broadly similar to the estimates based on the panel regression, particularly after accounting for the fact that the portfolios do not go as far out in the tail of the plan size distribution as the panel estimates.

Because we have fewer data points on the alternative asset classes, we also explore a specification that pools return data across all plans, alternative asset classes and years and imposes homogeneous slope coefficients:

$$\widetilde{r}_{iat} = c_a + \lambda_t + \beta_1 \log(\text{AUM}_{iat-1}) + \beta_2 \text{Private}_i + \beta_3 \text{nonUS}_i + \beta_4' x_{iat} + \epsilon_{iat}. \tag{6.3}$$

By assuming that the coefficients are the same across alternative asset classes, this specification uses far more data points which can increase the precision of our estimates. Results are shown in the "Alt" column of Table 7. We find a significantly positive relation between plans' log-AUM and policy-adjusted gross and net returns. Again, the coefficient on size is larger for net returns than for gross returns, consistent with some of the higher net returns earned by the largest plans stemming from their ability to better exploit economies of scale and reduce costs consistent with Hypotheses III(i)-(ii).

Given the significantly positive association between policy-adjusted net returns and

[40]For gross returns the magnitude is somewhat smaller, as we find increases of 26 bps (stocks), 2 bps (fixed income), 71 bps (hedge funds and multi assets), 303 bps (private equity), 75 bps (private debt), and 76 bps (real assets) per year.

[41]We use the 30th and 70th percentile instead of the 10th and 90th percentile to increase the number of observations within a year.

log-size observed for five out of six asset classes, we would also expect to find a positive and significant association between log-AUM and plans' total portfolio performance (i.e., the overall performance of a pension plan). We explore if this relation holds by estimating the following panel model for plan-level total portfolio returns:

$$\widetilde{r}_{it} = \lambda_t + \beta_1 \log(\text{AUM}_{it-1}) + \beta_2 \text{Private}_i + \beta_3 \text{nonUS}_i + \beta_4' x_{it} + \epsilon_{it}, \tag{6.4}$$

where $\widetilde{r}_{it}$ is the policy-adjusted return on plan i's total assets in year t, gross or net of costs. The "Total portfolio" column in Table 7 shows that larger plans obtain modestly higher policy-adjusted gross and net returns. For example, moving from the 10th to the 90th percentile plan as ranked by total AUM is associated with an increase in policy-adjusted net total-portfolio returns of 23 bps per annum.

6.2 Risk-adjusted Return Performance

Policy returns constitute a natural benchmark against which to measure individual plans' return performance. However, it is more common to measure investment performance by adjusting for plans' exposure to a small set of risk factors. Such an approach is not feasible here, however, because most plans have short return records in the CEM database.

As an alternative to conducting plan-level risk adjustments, for each asset class, we form equal-weighted portfolios that comprise up to 29 years of annual plan-level returns. We refer to this equal-weighted aggregate return for asset class A in year t as $\bar{r}_{At}$ and use it to estimate the following risk-adjustment regression:

$$\bar{r}_{At} - r_{ft} = \alpha_A + \beta_A' \text{F}_{At} + \epsilon_{At}, \tag{6.5}$$

where r_{ft} is the risk-free rate and F_{At} refers to the risk factors used for asset class A. We consider both the Fama and French (1993) three-factor model and the seven-factor model of Fung and Hsieh (2001) which includes the market excess return, a bond trend, currency trend, commodity trend, size spread, bond market and credit spread. The risk factor regressions provide a very good fit for stocks, fixed income, and hedge funds and a somewhat poorer fit for plans' returns in the three remaining alternative asset classes. Appendix D.4 provides further details.

Repeating the earlier analysis from Table 7 on the plan-year risk-adjusted returns, we find results that are broadly in line with those obtained for the policy-adjusted returns. The last four columns in Table 7 shows results for stocks, fixed income, alternative assets and the total portfolio. We find that the largest plans continue to produce significantly higher risk-adjusted returns on the alternative asset classes both on a gross and net of cost basis. Using risk-adjusted returns also leads to higher coefficient estimates on the size variable for fixed income and total portfolio returns.

7 Investment Management Style, Costs, and Return Performance

As we have described throughout this paper, pension plans must decide whether to manage their investments within a given sub-asset class internally or externally, as well as actively or passively. This decision reflects a variety of plan characteristics, particularly plan size (AUM) and sub-asset class, with some sub-asset classes lending themselves more easily to passive and internal management than others. In this section, we analyze how such decisions affect plan performance in the form of management costs and benchmark-adjusted returns. In doing so, we recognize that the estimation of the effect of plans' decisions on management styles and the resulting expected performance is endogenous. For example, a large plan might use its resources to identify a genuinely skilled external active manager, and bargain for lower fees rather than switching to lower-cost internal active management or even passive management. Plans may also switch management style because of external shocks affecting all plans within a given sub-asset class.

7.1 A Matching Estimator

We believe that a "gold standard" for estimation of the effect of plans' management style decisions on plan performance comes from the literature on treatment effects and matching estimators. The idea is to compare the performance in a given asset class of two otherwise similar plans where one plan switches from, say, external to internal management, while the other plan continues to manage its assets externally. Key to this type of matching estimator is, first, to obtain an accurate match, and, second, that there are a sufficient number of cases (switches) to allow us to accurately estimate any performance differences between the two types of plans. Provided that these conditions hold, the advantage of the resulting estimator is that, under a set of well-understood conditions, it controls for differences in any confounding factors that can vary across plans and asset classes.

Specifically, to account for the endogeneity of plans' asset management decisions and the presence of confounding factors, we adopt the difference-in-differences estimator recently proposed by Imai et al. (2021). The chief advantage of this estimator is that it can handle unbalanced panels such as ours and datasets with a small time-series dimension. It also allows units to switch treatment status over time. All of these are features we observe in the CEM data.

We use the effect of management style on plan cost as our lead example, but our analysis is parallel for policy-adjusted returns. First consider the effect of internal management on the cost (in bps) of plan i in sub-asset class a at time t, Cost_{iat}. Using the potential outcomes framework of Imbens and Rubin (2015), define the average effect of switching from external to internal management on management costs

$$\Delta C^{ex\to in} := \mathbb{E}\Big(\text{Cost}_{iat}(\text{Internal}_{iat} = 1, \text{Internal}_{iat-1} = 0) \\ - \text{Cost}_{iat}(\text{Internal}_{iat} = 0, \text{Internal}_{iat-1} = 0)|\text{Internal}_{iat} = 1, \text{Internal}_{iat-1} = 0\Big), \quad (7.1)$$

where $\text{Cost}_{iat}(\text{Internal}_{iat} = 1, \text{Internal}_{iat-1} = 0)$ is the potential cost outcome of a plan switching from external management at time $t-1$ to internal management at time t, whereas $\text{Cost}_{iat}(\text{Internal}_{iat} = 0, \text{Internal}_{iat-1} = 0)$ denotes the potential cost for the same plan not switching management style.[42]

To account for unobserved confounding variables such as bargaining power, we rely on the following parallel trend assumption

$$\mathbb{E}\left(\text{Cost}_{iat}(\text{Internal}_{iat} = 0, \text{Internal}_{iat-1} = 0) - \text{Cost}_{iat-1}|\text{Internal}_{iat} = 1, \text{Internal}_{iat-1} = 0, x_{iat}\right) \\ =\mathbb{E}\left(\text{Cost}_{iat}(\text{Internal}_{iat} = 0, \text{Internal}_{iat-1} = 0) - \text{Cost}_{iat-1}|\text{Internal}_{iat} = 0, \text{Internal}_{iat-1} = 0, x_{iat}\right). \quad (7.2)$$

In our analysis, x_{iat} contains the following time-varying (potentially confounding) controls:

- AUM_{iat}: total AUM allocated by plan i to sub-asset class a at time t
- Active_{iat}: an indicator for whether plan i manages sub-asset class a actively at time t
- Private_i: an indicator for whether plan i is private
- nonUS_i: an indicator for whether plan i is domiciled in the U.S.

[42] In the language of the treatment effect literature, Equation (7.1) represents the average treatment effect on the treated.

- sub-asset class a at time t.

The parallel trend assumption (7.2) stipulates that the change in management cost is equal between the treatment group (plans switching from external to internal management) and the control group (plans continuing with external management) in the absence of treatment ($\text{Internal}_{iat} = 0$), once we condition on x_{iat}. These observed variables allow us to control for differences in costs induced by plan size (captured by AUM_{iat}), active vs. passive management (captured by Active_{iat}), public vs. private plans (captured by Private_i), U.S. vs. non-U.S. plans (captured by nonUS_i), and sub-asset class heterogeneity. We include the latter as a control to impose that plans can only be matched within the same sub-asset class because of the large heterogeneity in costs (and potential confounding variables) across different sub-asset classes.[43] Intuitively, our matching approach can therefore be thought of as providing an estimate of the "pure" effect on cost of choosing internal management as opposed to external management after controlling for plan size, differences across sub-asset class, and other plan characteristics.

We also consider estimating the reverse effect of a switch from internal to external management:

$$\Delta C^{in\to ex} := \mathbb{E}\Big(\text{Cost}_{iat}(\text{External}_{iat} = 1, \text{External}_{iat-1} = 0) \\ - \text{Cost}_{iat}(\text{External}_{iat} = 0, \text{External}_{iat-1} = 0) | \text{External}_{iat} = 1, \text{External}_{iat-1} = 0\Big),$$

where $\text{Cost}_{iat}(\text{External}_{iat} = 1, \text{External}_{iat-1} = 0)$ is the potential cost outcome of a plan switching from internal management at time $t-1$ to external management at time t, whereas $\text{Cost}_{iat}(\text{External}_{iat} = 0, \text{External}_{iat-1} = 0)$ denotes the cost for the same plan that sticks with internal management.

7.2 Cost Estimates

We begin our analysis by applying the matching estimator to the cost data. Results from the matching estimator are shown in Panel A of Table 8. We find that switching from

[43] Note that the parallel trend assumption rules out potentially time-varying omitted confounding variables that affect both management costs and the choice of external management. Once the set of potentially confounding variables is specified, treatment and control units are matched based on their propensity score, which is a measure of how similar the plans are along the variables contained in x_{iat}. Finally, an estimate of the effect of internal management on cost is obtained by forming an average between treatment and control units in the matched set. See Imai et al. (2021, Equation 18). We use the `PanelMatch` package in `R` developed by these authors to carry out the estimation.

external to internal management (top row) is associated with substantial cost savings, especially in private asset classes. For stocks and fixed income, a change from external to internal management leads to a decrease in cost of 3 bps/year and 5 bps/year, respectively, while, in private markets, cost savings are 320 bps/year (private equity), 26 bps/year (private debt), and 47 bps/year (real assets).[44] Aggregating across all alternative asset classes, we obtain an estimate of 56 bps/year in cost savings. When pooling all asset classes ("All") we obtain a cost savings estimate a little over 4 bps/year. This estimate is closer to the savings for the public asset classes, reflecting their importance in plans' portfolios.

In the data, there are also a number of plans that switch from internal to external management. We analyze the effect on cost of this reverse switch using the same methodology. Panel A of Table 8 shows that costs significantly increase when plans switch from internal to external management. Management costs increase by 7 bps/year for stocks, 5 bps/year for fixed income, and by 24–96 bps/year in the alternative asset classes. Across the alternative asset classes, a switch from internal to external asset management is associated with a 54 bps/year increase in costs – essentially mirroring the cost savings estimate (55 bps/year) for the reverse external-to-internal switch. Interestingly, the total portfolio-level increase in costs associated with a switch from internal to external management is somewhat higher than the cost savings associated with the reverse switch (18 bps versus 4 bps).

In summary, our matching estimates indicate that switching from external to internal asset management leads to modest cost savings for public asset classes, but very large cost savings for private asset classes, while the reverse shift from internal to external asset management leads to modestly higher costs for stocks and bonds and significantly higher management costs for alternative assets. We note that the smaller cost savings for public asset classes are multiplied by the large allocations of DB plans to them.

We next consider the effect on costs of switching between active and passive management. We limit our analysis to the three asset classes (stocks, fixed income, and real assets) for which we have a sufficiently large number of transitions to facilitate accurate estimation. Our estimates are shown in the three rightmost columns of Table 8.[45] We find that switching from active to passive management reduces costs by around 9 bps/year

[44] We omit hedge funds and and multi-assets since our sample contains too few plans in these asset classes that switch between external and internal management.

[45] We use the same set of potentially confounding variables x_{iat} as for the internal/external estimates, except we replace Active_{iat} with External_{iat} to control for heterogeneity in costs associated with external management.

for stocks and real assets and by 2 bps/year for fixed income, consistent with the low overall level of fees for this asset class. All estimates are statistically significant.

Conversely, a switch from passive to active management leads to a significant increase in costs. As before, the estimated effect is most pronounced for stocks (15 bps/year) and real assets (16 bps/year), and smaller for fixed income (5 bps/year).

7.3 Return Performance

To analyze the effect of internal versus external and active versus passive management on return performance, we adopt our matching methodology to policy-adjusted returns. In this case, we use as conditioning variables the previous year's AUM in sub-asset class a (AUM_{iat-1}), as well as the current sub-asset class for matching to ensure that treated and control observations have similar covariate values.[46]

Panel B of Table 8 shows that a switch from external to internal management leads to a significant increase in gross and net return performance for all asset classes, except private debt, where the estimate is insignificant due to a very small number of transitions. In all cases, the effect is larger for net returns due to the associated decrease in cost. For stocks and fixed income, a switch from external to internal management is accompanied by an increase in net policy-adjusted returns of 108 bps/year and 47 bps/year, respectively. For two of the three private asset classes, the effect is more pronounced, with increases in policy-adjusted net returns of 255 bps/year (private equity) and 194 bps/year (real assets). For alternative asset classes as a whole, switching from external to internal asset management is associated with an increase in net returns of 198 bps/year. Similarly, when pooling all asset classes, the estimated effect on net portfolio-level returns from switching from external to internal management is 93 bps/year. We note that these yearly increases in return performance, for plans that move from external to internal management, are consistent with the need for such plans to justify the fixed costs of setting up internal management.

The bottom rows of Panel B in Table 8 also show the effect of changing from internal to external management. For the alternative asset classes, we find a *decrease* in return performance, both gross and net of fees ranging from -578 bps/year to -60 bps/year for net return performance in private equity and real assets, respectively. Overall, across all alternative asset classes, we find a decline in net return performance of 202 bps/year

[46] I.e., we impose that treatment and control units are only matched within the same sub-asset class, as in Section 7.1.

which, again, mirrors the estimate (198 bps) from the reverse switch.

The deterioration in return performance from a switch toward external management does not carry over to public asset classes. Instead, we find that a switch from internal to external management raises average net policy-adjusted returns by 139 bps/year for stocks, and by 26 bps/year for fixed income, although the latter estimate is insignificant.

For the total portfolio, our estimate suggests a small and statistically insignificant improvement of 22 bps/year in net return performance following a switch from internal to external asset management. This is substantially lower than the improvement of 93 bps/year observed for the reverse switch (external to internal management).

These results suggest the following. First, for private asset classes, we observe significant improvements in return performance (both net and gross of costs) associated with a switch from external to internal management while, conversely, return performance is significantly decreased following the reverse switch from internal to external management. Hence, return performance in alternative asset classes has benefited significantly from plans switching from external to internal asset management. A significant driver of this is cost savings, but we also observe large improvements in gross returns following the adoption of internal management for private equity and real assets.

Next, for public asset classes, and stocks in particular, a switch in management style (from external to internal or internal to external) is likely driven by poor prior-year performance. If such switches are driven by poor return performance in year $t-1$, mean-reversion in performance would dictate that we should expect to see improved performance in year t. Consistent with this explanation, we find underperformance of -140 bps/year in the year prior to the switch for plans that move from internal to external management. For comparison, plans in the control group have a slight outperformance of 50 bps during this period. This suggests that the parallel trend assumption in (7.2) is violated for plans that switch from internal to external management.[47] Moreover, if we extend the set of conditioning variables to include net returns in year $t-1$, the estimate of the effect on net stock returns declines from 139 bps/year to 12 bps/year.

The fact that we do not observe a similar effect for the alternative asset classes may reflect that the improvement in return performance associated with internal management is much larger and, also, that asset values are not marked-to-market in the same way as for the public asset classes. Cost savings from internal asset management are also much larger for the alternative asset classes, as we have seen.

Last, we apply our matching methodology to estimate the effect of passive and ac-

[47] We see no similar violation of this assumption for fixed income.

tive management on policy-adjusted returns.[48] The three rightmost columns in the top rows of Table 8 (Panel B) show that a switch from active to passive management does not significantly increase gross or net return performance with signs being both negative (stocks) and positive (fixed income, real assets). A switch from passive to active management (bottom rows) is, however, associated with a significantly negative policy-adjusted net return of -36 bps/year for stock investments. Policy-adjusted return estimates for a switch from passive to active management are also negative both gross and net of costs for fixed income and real assets, but fail to be statistically significant.

Our findings suggest that changes from active to passive or from passive to active management are, on the whole, not associated with a significant effect on plans' gross or net policy-adjusted return performance. This is consistent with an equilibrium in which competition is so strong among active managers (in public asset classes in particular) that fees are set so that, for the marginal plan that decides to switch, a very small change in performance can be expected.[49]

8 Conclusion

This paper explores the relation between pension plan size and allocations to active vs. passive management, internal vs. external management, and public vs. private market investments. Consistent with fixed costs being important in setting up internal investment management capabilities, large plans *internally* manage a significantly greater proportion of assets than their smaller peers. Similarly, taking advantage of their greater ability to identify internal and external investment opportunities in the less transparent markets for private assets, large plans also allocate more of their holdings to asset classes such as private equity and real assets and less to (public) stocks and fixed income.

Our results indicate a strong role for economic scale in pension plan fees and investment performance: investment management costs follow a power law with cost economies being particularly strong for passively managed accounts and public asset classes. Hence, large plans pay significantly lower fees per dollar invested than their smaller peers. While large plans' better ability to identify skilled external managers and negotiate lower fees has only translated into modestly higher net-of-cost return performance in the highly

[48] The set of controls used is identical to those listed in Section 7.2.

[49] Notice that this finding does not contradict our earlier result that large plans tend to get better return performance, particular net of costs. The matching estimates in Table 8 control for plan size and are based on the population of plans that switch between active and passive management. Hence, they characterize the return effect for the marginal plan that switches management style.

competitive public asset markets (stocks and fixed income), we find strong evidence that larger plans earn economically large and significant abnormal returns in the markets for private assets (again, compared to their smaller peers). Private markets are less transparent and so allow the largest plans to benefit from their comparative advantage in searching for skilled managers.

The scale disadvantages in investment management costs that we identify for smaller plans indicate that these plans may perform best when they embrace passive management which is widely available in public asset markets. For private asset classes, passive management is generally not an option (other than for special cases such as REITS) and fixed costs are too high to be covered by small plans which, consequently, rely almost entirely on external active management and have to accept the higher management fees typically charged for this service. Conversely, large plans have the ability to manage private assets internally and negotiate lower external investment management fees. This helps explain why plan size (scale) is particularly important in determining investment performance in private asset markets and why private asset classes have become particularly important for large plans in recent years.

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	Small Plans (in %)				Large Plans (in %)			
Stocks	IP	EP	IA	EA	IP	EP	IA	EA
ACWI x. US	1.66	27.51		70.82	2.77	31.00	2.77	63.45
EAFE		19.95	1.44	78.62	18.53	14.94	11.99	54.55
Emerging		13.50		86.50	15.02	8.65	13.54	62.79
Global		24.74	1.14	74.12	15.19	6.00	58.51	20.29
Other					25.74	0.62	26.75	46.90
U.S. Broad	14.17	57.90	2.06	25.87	34.06	32.08	8.55	25.31
U.S. Large Cap		51.88	11.45	36.67	32.05	31.53	20.02	16.40
U.S. Mid Cap		34.60		65.40	27.54	6.15	25.06	41.25
U.S. Small Cap		18.50		81.50	19.66	4.87	13.25	62.22
Fixed Income								
Bundled LDI		1.61	37.56	60.83	28.22	45.20	2.66	23.92
Cash			54.70	45.30				100.00
Convertibles				100.00				100.00
EAFE					86.88			13.12
Emerging				100.00	7.51	6.21	23.91	62.37
Global		0.60		99.40	8.84	0.63	82.76	7.77
High Yield			5.87	94.13		3.59	23.03	73.37
Inflation Indexed	24.63	48.74	9.87	16.77	40.47	11.61	41.33	6.60
Long Bonds	0.32	21.33	5.46	72.88	18.54	0.58	14.46	66.43
Other		14.44	14.54	71.02	72.48	0.88	7.01	19.63
U.S.		13.18	2.75	84.07	6.27	10.37	46.22	37.14
Hedge & multi ass.								
Funded TAA			6.05	93.95			58.27	41.73
Hedge Fund				100.00				100.00
Risk Parity				100.00			28.19	71.81
Private Equity								
Div. Private Eq.			0.08	99.92			18.86	81.14
LBO				100.00			0.27	99.73
Other				100.00			26.81	73.19
Venture Capital				100.00			0.70	99.30
Private Credit								
Mortgages			1.98	98.02			67.24	32.76
Credit			10.49	89.51			31.45	68.55
Real Assets								
Commodities		18.43		81.57	19.70	1.82	58.20	20.28
Infrastructure				100.00			61.39	38.61
Nat. Resource				100.00			46.70	53.30
Other				100.00			28.42	71.58
Real Estate			2.62	97.38			39.67	60.33
REIT		6.60		93.40	2.53	3.59	77.54	16.33

Table 1: **Small and large plans' investment allocation by sub-asset class and management structure in 2019**. This table shows the share (in %) of AUM allocated to the four management mandates: Internal Passive (IP), External Passive (EP), Internal Active (IA), and External Active (EA) for the given sub-asset classes. The share is calculated as follows: $\omega_{ats} = \frac{\text{AUM}_{ats}}{\text{AUM}_{at}}$, where $\text{AUM}_{ats} = \sum_i \text{AUM}_{iats}$, and $\text{AUM}_{at} = \sum_s \sum_i \text{AUM}_{iats}$, where i denotes plan i, a indicates the sub-asset class, t denotes the year 2019, and s denotes one of the four mandates. The shares are calculated separately for small and large plans, defined by the bottom and top 30th percentile of AUM in 2019 respectively. For small and large plans, rows sum up to 100%.

Panel A: Panel and Cragg Estimation

	Stocks		Fixed Income		Hedge & Multi ass.		Private Equity		Private Debt		Real Assets	
	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE
$\log(\text{AUM}_{it-1})$	**8.29**	**11.24**	**10.96**	**17.66**	**0.82**	0.68	**2.34**	**2.32**	**11.25**	**14.31**	**6.80**	**6.40**
	(0.824)	(2.461)	(0.997)	(2.647)	(0.397)	(0.454)	(0.787)	(0.825)	(2.360)	(5.034)	(0.990)	(1.540)
$\text{CostSpread}^{E-I}_{iAt-1}$	**15.25**	12.23	**23.81**	**30.29**	-0.00	0.17	-0.09	-0.23	-0.01	-0.95	1.03	2.66
	(5.245)	(6.946)	(4.784)	(8.660)	(0.189)	(0.420)	(0.061)	(0.240)	(0.087)	(1.729)	(0.623)	(1.576)
Private_i	-0.29	1.65	-3.36	2.36	0.43	-0.89	1.81	3.50	6.54	15.27	0.29	2.21
	(2.067)	(4.260)	(2.845)	(6.810)	(0.851)	(1.377)	(1.535)	(2.906)	(7.181)	(12.758)	(2.469)	(3.204)
NonUS_i	**13.99**	**13.06**	**23.60**	**21.91**	0.74	-0.83	**14.45**	**11.91**	**22.23**	1.88	**27.79**	**17.44**
	(2.097)	(4.596)	(2.759)	(5.387)	(1.232)	(1.196)	(2.512)	(4.490)	(7.275)	(9.156)	(2.964)	(3.814)
Obs	7205	7205	7222	7222	1944	1944	4322	4322	1055	1055	5676	5676
R^2	0.26		0.29		0.06		0.18		0.30		0.24	

Panel B: Cragg Selection Estimates

	Stocks	Fixed Income	Hedge & Multi ass.	Private Equity	Private Debt	Real Assets
$\log(\text{AUM}_{it-1})$	**38.19**	**28.49**	**33.07**	**23.59**	**34.59**	**28.08**
	(4.018)	(3.309)	(8.783)	(5.709)	(8.935)	(4.227)
$\text{CostSpread}^{E-I}_{iAt-1}$	36.77	21.52	**-13.33**	-2.30	-2.32	0.20
	(23.892)	(18.451)	(5.741)	(1.712)	(4.065)	(2.617)

$\Pr(\omega^{internal}_{iAt} > 0 \mid X = x)$

Plan size	Stocks	Fixed Income	Hedge & Multi ass.	Private Equity	Private Debt	Real Assets
10^{th} percentile	13.22	28.85	0.50	5.60	9.26	12.82
50^{th} percentile	34.35	48.97	2.51	12.54	24.86	27.08
90^{th} percentile	66.18	72.12	10.59	26.06	52.56	49.71

Table 2: **Asset allocation regression for internal vs. external management**. **Panel A** of this table presents estimates of the regression (4.6): $\omega^{internal}_{iAt} = c_A + \lambda_{At} + \beta_{1,A}\log(\text{AUM})_{it-1} + \beta_{2,A}\text{CostSpread}^{E-I}_{iAt-1} + \beta_{3,A}\text{Private}_i + \beta_{4,A}\text{nonUS}_i + \epsilon_{iAt}$, where $\omega^{internal}_{iAt}$ is the share of AUM that is internally managed by plan i in asset class A at time t, λ_{At} is a time fixed effect, AUM_{it-1} denotes the lagged AUM of sponsor i, $\text{CostSpread}^{E-I}_{iAt-1}$ is plan i's cost spread between external and internal management in asset class A at time $t-1$, Private_i is a dummy equal to one if plan i is private, and nonUS_i is a dummy equal to one if the plan is domiciled outside the U.S. For each asset class we also use the Cragg estimator with a point mass at 0. We report the average partial effects of Cragg estimates in columns named "Cragg APE". In case a plan is fully internal (external) we impute the external (internal) cost as the median cost from plans that are similar in size, where size in a given year is either small (bottom 30th percentile), medium (between 30th and 70th percentile), or large (top 70th percentile) of total AUM. Robust standard errors are in parenthesis and clustered by plan. Boldface coefficients are statistically significant at the 5% level. The asset class "Private Debt" does not include time fixed effects due to the small sample size, and estimation for "Hedge Funds" start in 2000 due to lack observation prior to 2000. **Panel B** presents the results of the Cragg selection equation (4.2a). The bottom part of panel B shows the probability of allocating at least some portion of investments internally. We fix the the cost spread at the mean cost spread across time and sponsors, and show the different probabilities based on size, using the 10th, 50th, and 90th percentile of AUM in 2019 in a given asset class. All coefficients and standard errors are multiplied by 100.

Panel A: Internal vs. External Management						
	Stocks	Fixed Income	Hedge multi ass.	Private Equity	Private Debt	Real Asset
log(AUM)						
Percentile: 10	**3.75**	**6.47**	0.44	**0.41**	**6.57**	**2.55**
	(0.875)	(1.060)	(0.241)	(0.208)	(1.910)	(0.499)
Percentile: 90	**31.90**	**43.80**	0.69	1.70	20.10	**6.22**
	(9.860)	(10.500)	(0.796)	(1.090)	(10.800)	(2.190)
Difference	**28.15**	**37.33**	0.25	1.29	13.53	3.67
Cost Spread						
Percentile: 10	**9.40**	**21.50**	0.19	-0.09	-0.96	**1.35**
	(4.640)	(5.230)	(0.281)	(0.104)	(1.770)	(0.554)
Percentile: 90	12.20	**28.60**	0.16	-0.08	-0.92	1.82
	(7.610)	(8.740)	(0.474)	(0.081)	(1.630)	(0.986)
Difference	2.8	**7.10**	-0.04	0.01	0.03	0.47
Obs	7205	7222	1944	4322	1055	5676

Panel B: Active vs. Passive Management					
	Active Overall			Active Int. vs. Ext.	
	Stocks	Fixed Income	Real Asset	Stocks	Fixed Income
log(AUM)					
Percentile: 10	**-4.60**	2.76	-0.07	**3.80**	**5.87**
	(0.720)	(1.630)	(0.353)	(0.114)	(0.105)
Percentile: 90	**-4.16**	**2.08**	0.18	**17.30**	**38.30**
	(1.340)	(0.624)	(0.231)	(0.789)	(0.993)
Difference	0.44	-0.68	0.25	13.5	**32.43**
Cost Spread					
Percentile: 10	**-30.30**	**-19.40**	-0.11	1.26	**18.50**
	(4.470)	(5.570)	(0.326)	(3.980)	(4.380)
Percentile: 90	**-39.70**	**-25.80**	-0.11	1.15	**24.60**
	(8.310)	(9.740)	(0.376)	(4.510)	(7.20)
Difference	**-9.40**	-6.4	-0.01	-0.11	**6.10**
Obs	7206	7210	4395	7012	7090

Table 3: **Significance test for the difference in APE for size and cost spread.** This table shows the APE (4.7) estimated for size ($\log \mathrm{AUM}_{it-1}$) and external minus internal cost spread (Panel A). In Panel B we calculate two different cost spreads. For "Active Overall", we define the cost spread to be active minus passive for the given asset class, and for " Active Int. vs. Ext", we define the cost spread as Active external minus active internal. We set $\log(\mathrm{AUM})_{it-1}$ and $\mathrm{CostSpread}_{iAt-1}$ to their 10^{th} and 90^{th} percentile values in 2019 respectively. Then we test if the estimated APEs are equal using a χ^2-test. We report the difference of the calculated APEs. Panel A uses the proportion of plans' holdings within each asset class that is internally managed as the dependent variable. Panel B uses either the proportion of plans' holdings within each asset class that is actively managed (columns 1-3) or the proportion of internally managed assets that is managed actively as the dependent variable (columns 4-5). The columns show the calculation for each asset class. All coefficients and standard errors are multiplied by 100. We compute the standard errors of the computed APEs using the Delta method and standard errors are reported in parenthesis. Boldface coefficients are significant at the 5% level.

	Active Allocation						Active Internal Allocation			
	Stocks		Fixed Income		Real Assets		Stocks		Fixed Income	
	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE	Panel	Cragg APE
$\log(\text{AUM}_{it-1})$	**-3.20**	**-4.27**	0.08	**2.45**	-0.11	0.04	**6.43**	**8.25**	**10.22**	**16.81**
	(0.675)	(0.827)	(0.658)	(1.231)	(0.160)	(0.318)	(0.833)	(2.333)	(1.036)	(2.675)
$\text{CostSpread}_{iAt-1}$	**-20.47**	**-32.87**	**-7.36**	**-22.23**	-0.01	-0.11	**8.10**	1.50	**17.52**	**27.02**
	(4.019)	(5.663)	(3.586)	(9.363)	(0.193)	(0.349)	(3.865)	(4.988)	(4.260)	(7.701)
Private_i	3.13	**4.79**	-1.94	2.01	-0.15	0.18	1.03	3.52	-4.27	-0.55
	(1.997)	(2.263)	(2.041)	(2.561)	(0.845)	(0.729)	(2.072)	(4.718)	(2.824)	(6.661)
NonUS_i	**4.64**	1.56	**-8.93**	**-9.75**	0.40	**1.47**	**14.94**	**16.10**	**24.28**	**24.54**
	(2.098)	(2.227)	(2.139)	(2.678)	(0.739)	(0.664)	(2.230)	(6.019)	(2.828)	(5.217)
Constant	0.57		-7.73		-0.42		**-42.72**		**-59.85**	
	(5.874)		(6.038)		(2.089)		(5.948)		(7.976)	
Obs	7206	7206	7210	7210	4395	4395	7012	7012	7090	7090
R^2	0.10		0.04		0.01		0.18		0.27	

Table 4: **Asset allocation regression for passive vs. active management**. The left panel shows the regression of the fraction of actively managed assets over total assets for stocks, fixed income and real assets as shown in equation (4.8). In the four rightmost columns the dependent variable is defined as the proportion of actively managed assets that is internally managed: $\text{AUM}_{iAt}^{Active,Internal}/\text{AUM}_{iAt}^{Active}$. For each asset class the regression specification is as follows. We include the log of year t - 1 AUM per sponsor, and the cost spread between active and passive at year $t-1$. For the rightmost columns the cost spread is defined as the difference between active external minus active internal cost. For cases where a plan is fully internal (external) we impute the external (internal) cost as the median cost for plan that is similar size (small (30^{th} percentile in total AUM), medium (between 30^{th} and 70^{th} percentile in total AUM), or large (70^{th} percentile in total AUM)) in that given year. We include a dummy that equals 1 if the plan is private (Private_i), and a dummy that equals 1 if the plan is located outside of the U.S. (nonUS_i). Lastly, we control for time fixed effects. For each asset class we run two regressions, namely a time fixed effects panel regression and a hurdle regression with a point a mass at 1. The column heading "Panel" denotes the fixed effects regression estimates. We report the average partial effects (APE) of Cragg estimates in columns starting with "Cragg". Robust standard errors are in parenthesis and clustered by plan. Boldface coefficients are statistically significant at the 5% level. All coefficients and standard errors are multiplied by 100.

Panel A	Stocks	Fixed Income	Hedge & multi ass.	Private Equity	Private Debt	Real Assets
$\log(\text{AUM}_{it-1})$	**-2.08**	**-0.87**	**-1.85**	**0.44**	**-0.40**	**0.65**
	(0.339)	(0.324)	(0.271)	(0.157)	(0.168)	(0.130)
Cost_{iAt-1}	**-7.11**	**-20.10**	**-1.65**	**-0.11**	0.01	**-0.44**
	(3.109)	(4.341)	(0.430)	(0.029)	(0.012)	(0.097)
Private_i	**-2.90**	**5.94**	-1.73	-0.33	-0.99	**-2.03**
	(0.920)	(0.858)	(0.940)	(0.434)	(0.589)	(0.294)
nonUS_i	**-3.38**	**2.66**	**-3.75**	**-2.09**	0.12	**1.66**
	(0.930)	(0.934)	(0.939)	(0.413)	(0.656)	(0.379)
Obs	7206	7219	2611	4413	1073	5677
R^2	0.24	0.12	0.15	0.20	0.10	0.31
Panel B						
$\log(\text{AUM}_{it-1})$	**-2.50**	-0.65	**-1.84**	**0.60**	**-0.43**	**0.72**
	(0.423)	(0.388)	(0.336)	(0.157)	(0.176)	(0.182)
Cost_{iAt-1}	**-8.92**	**-15.49**	**-1.37**	**-0.09**	0.01	**-0.58**
	(3.558)	(4.274)	(0.467)	(0.027)	(0.010)	(0.123)
Private_i	**-4.46**	**8.78**	-1.74	-0.42	-0.96	**-2.51**
	(1.088)	(0.977)	(1.061)	(0.440)	(0.629)	(0.370)
nonUS_i	**-2.48**	**2.57**	**-4.17**	**-2.19**	-0.03	**1.65**
	(1.210)	(1.169)	(1.126)	(0.408)	(0.681)	(0.493)
$\text{LiabilityRetiree}_{it}$	**-6.00**	2.48	1.64	1.11	1.90	-0.56
	(3.026)	(3.354)	(2.434)	(1.184)	(1.680)	(1.028)
Obs	4435	4440	1757	2774	782	3499
R^2	0.27	0.16	0.14	0.22	0.11	0.30

Table 5: **Asset allocation regression**. This table reports estimates of the regression (4.9): $\omega_{iAt} = c_A + \lambda_{At} + \beta_{1,A}\log(\text{AUM}_{it-1}) + \beta_{2,A}\text{Cost}_{iAt-1} + \beta_{3,A}\text{Private}_i + \beta_{4,A}\text{nonUS}_i + \beta_{5,A}\text{LiabilityRetiree}_{it} + \epsilon_{iAt}$, where ω_{iAt} denotes plan i's proportion of assets allocated to asset class A at time t, c_A is the asset class fixed effect, λ_{At} denotes the time fixed effect, $\log(\text{AUM}_{it-1})$ denotes the log of plan i's total AUM at time $t-1$, Cost_{iAt-1} denotes the cost (in bps) of plan i in asset class A at time $t-1$, Private_i denotes a dummy variable equal to one if plan i is not a public plan, nonUS_i is a dummy variable equal to one if the plan is domiciled outside the U.S., and $\text{LiabilityRetiree}_{it}$ denotes the fraction of plan i's total liabilities owed to retirees in year t. **Panel A** excludes $\text{LiabilityRetiree}_{it}$ as a regressor. All coefficient estimates and standard errors are multiplied by 100. The robust standard errors are in parenthesis and clustered by plan. Boldface coefficients are statistically significant at the 5 percent level.

	Regression					Size percentile		
	$\log(\text{AUM}_{iats})$	Private_i	nonUS_i	Obs	R^2	10%	50%	90%
Stocks								
IP	**0.76**	0.25	**0.93**	2294	0.70	2.67	1.48	0.85
	(0.037)	(0.157)	(0.120)					
EP	**0.75**	-0.01	**0.24**	11239	0.62	5.39	2.94	1.65
	(0.015)	(0.051)	(0.055)					
IA	**0.89**	**0.46**	0.22	3552	0.70	9.36	7.25	5.62
	(0.027)	(0.167)	(0.148)					
EA	**0.88**	**0.04**	**-0.28**	25799	0.86	62.66	49.98	39.11
	(0.007)	(0.021)	(0.023)					
Fixed Income								
IP	**0.80**	-0.09	**0.39**	1269	0.69	2.94	1.51	1.00
	(0.047)	(0.210)	(0.175)					
EP	**0.79**	0.11	**0.26**	4125	0.63	4.57	2.84	1.92
	(0.024)	(0.071)	(0.074)					
IA	**0.84**	**0.51**	**0.25**	5293	0.72	4.09	2.77	2.03
	(0.021)	(0.124)	(0.103)					
EA	**0.94**	0.00	**-0.18**	17544	0.76	27.75	23.98	20.92
	(0.010)	(0.036)	(0.040)					
Hedge & Multi ass.								
EA	**0.95**	0.09	-0.03	4801	0.78	146.87	133.21	120.66
	(0.018)	(0.062)	(0.064)					
Private Equity								
IA	1.01	0.19	0.37	768	0.78	18.00	18.49	19.02
	(0.035)	(0.215)	(0.241)					
EA	**0.93**	**-0.08**	0.02	8480	0.86	382.93	312.52	268.04
	(0.015)	(0.039)	(0.050)					
Private Debt								
IA	0.95	-0.39	**0.76**	411	0.79	12.25	10.13	8.64
	(0.064)	(0.274)	(0.286)					
EA	0.94	-0.18	**-0.62**	1377	0.75	188.03	165.91	146.75
	(0.036)	(0.147)	(0.139)					
Real Assets								
IA	1.01	0.00	**0.49**	2211	0.74	11.58	11.79	11.98
	(0.032)	(0.138)	(0.135)					
EA	**0.92**	-0.06	-0.07	12117	0.79	161.87	136.15	115.65
	(0.011)	(0.036)	(0.037)					

Hypothesis Testing (p-value)					
Null hypothesis	Stocks	Fixed Income	Private Equity	Private Debt	Real Assets
$\beta^{\text{IP}} = \beta^{\text{EP}}$	0.90	0.46			
$\beta^{\text{IA}} = \beta^{\text{EA}}$	0.19	**0.00**	0.33	0.79	**0.01**
$\beta^{\text{P}} = \beta^{\text{A}}$	**0.00**	**0.00**			

Table 6: **Economies of scale for cost among different investment mandates.** The *regression* panel of this table shows estimates of the model (5.2): $\log(\text{Cost}^{\$}_{iats}) = c_{As} + \lambda_{Ats} + \beta_{As}\log(\text{AUM}_{iats}) + \gamma_{1,As}\text{Private}_i + \gamma_{2,As}\text{nonUS}_i + \varepsilon_{iats}$, where $\text{Cost}^{\$}_{iats}$ is the cost (in dollars) of plan i in sub-asset class a at time t for mandate s, c_{As} is a constant that varies with asset class A and mandate s, λ_{Ats} is the time fixed effect for asset class A and mandate s, $\log(\text{AUM}_{iats})$ is the log of total AUM of plan i in sub-asset class a at time t for mandate s, Private_i is a dummy equal to one if plan i is private and nonUS_i is a dummy equal to one if plan i is located outside the U.S. For stocks and fixed income, we estimate the panel separately for the following mandates s: Internal Passive (IP), Internal Active (IA), External Passive (EP) and External Active (EA). The boldface coefficients on log(AUM) are significantly different from one at the 5% level and boldface coefficients on the other coefficients are significantly different from zero. Robust standard errors are reported in parenthesis and are clustered by plan. The *size percentile* columns show $\widehat{\text{Cost}}^{\$}_{iats}/\text{AUM}_{iats}$ in bps, where $\widehat{\text{Cost}}^{\$}_{iats}$ is predicted based on the *regression* panel. We set Private_i and nonUS_i equal to zero and use the 10^{th}, 50^{th} and 90^{th} percentile of AUM_{iats} in 2019 to obtain the fraction of cost relative to AUM. The bottom panel shows p-values of the null hypotheses that returns to scale are the same for different mandates, where a boldface p-value indicates a rejection of the null hypothesis.

	Policy-Adjusted Returns								Risk-Adjusted Returns			
Panel A	Stocks	Fixed income	Hedge & multi ass.	Private equity	Private debt	Real assets	Alt.	Total portfolio	Stocks	Fixed income	Alt.	Total portfolio
Gross												
$\log(\text{AUM}_{iat-1})$	**0.06**	0.00	0.18	**0.63**	0.12	**0.16**	**0.29**	**0.04**	-0.03	**0.17**	**0.36**	**0.14**
	(0.026)	(0.031)	(0.093)	(0.133)	(0.123)	(0.080)	(0.059)	(0.020)	(0.048)	(0.054)	(0.127)	(0.039)
Private_i	**0.17**	0.06	0.52	-0.21	-0.41	0.36	0.17	**0.11**	0.16	**1.22**	-0.63	**0.40**
	(0.075)	(0.064)	(0.326)	(0.495)	(0.377)	(0.240)	(0.207)	(0.052)	(0.129)	(0.141)	(0.400)	(0.103)
nonUS_i	-0.14	**-0.23**	**-0.68**	**2.19**	0.01	0.02	**0.45**	-0.02				
	(0.096)	(0.086)	(0.323)	(0.563)	(0.418)	(0.253)	(0.218)	(0.063)				
Obs	22879	18042	2762	4984	1015	8819	17580	7181	3897	3721	6298	4907
R^2	0.07	0.05	0.20	0.21	0.18	0.08	0.09	0.19	0.00	0.02	0.01	0.01
Net												
$\log(\text{AUM})_{iat-1}$	**0.09**	0.03	**0.28**	**0.86**	0.14	**0.25**	**0.43**	**0.06**	-0.00	**0.19**	**0.46**	**0.16**
	(0.026)	(0.031)	(0.091)	(0.126)	(0.123)	(0.084)	(0.061)	(0.019)	(0.047)	(0.054)	(0.135)	(0.041)
Private_i	0.14	0.06	0.46	0.23	-0.28	0.46	0.34	0.10	0.13	**1.20**	-0.57	**0.37**
	(0.075)	(0.063)	(0.325)	(0.481)	(0.374)	(0.244)	(0.208)	(0.051)	(0.129)	(0.139)	(0.412)	(0.109)
nonUS_i	-0.09	**-0.22**	**-0.64**	**2.15**	0.20	0.24	**0.56**	0.09				
	(0.095)	(0.083)	(0.324)	(0.534)	(0.417)	(0.258)	(0.215)	(0.060)				
Obs	22878	18042	2762	4986	1015	8819	17582	7181	3897	3721	6300	4907
R^2	0.06	0.04	0.15	0.19	0.13	0.06	0.06	0.13	0.00	0.02	0.01	0.01
Panel B												
Panel reg.	Mean return increase: moving from the 10th to 90th plan size percentile in 2019											
Gross	0.26	0.02	0.71	3.03	0.75	0.76	1.39	0.18				
Net	0.41	0.13	1.09	4.19	0.79	1.22	2.02	0.23				
Portfolio sort	Mean return increase: moving from the 30th to 70th plan size percentile											
Gross	0.21	0.02	0.39	3.33	0.10	0.90						
	(0.379)	(0.177)	(0.983)	(2.056)	(0.804)	(0.581)						
Net	0.39	0.14	0.79	**4.25**	0.43	**1.26**						
	(0.380)	(0.176)	(0.923)	(2.073)	(0.790)	(0.592)						

Table 7: **Regression of policy- and risk-adjusted returns on plan characteristics**. This table shows estimates of model (6.2): $\widetilde{r}_{iat} = c_a + \lambda_{At} + \beta_{1,A}\log(\text{AUM}_{iat-1}) + \beta_{2,A}\text{Private}_i + \beta_{3,A}\text{nonUS}_i + \beta'_{4,A}x_{iat} + \epsilon_{iat}$, where $\widetilde{r}_{iat}$ denotes the policy-adjusted **gross** (top) and **net** (bottom) return; $\log(\text{AUM}_{iat-1})$ denotes plan i's total AUM in sub-asset class a at time $t-1$; Private_i is a dummy for whether a plan is private; nonUS_i is a dummy for whether plan i is domiciled in the U.S.; x_{iat}, a set of controls including the fraction of external and active management, as well as a performance fee dummy. The column "Alt." estimates (6.3) and pools the alternative asset classes: Hedge & multi assets, Private equity, Private debt and Real assets. The column *Total portfolio* uses plan-level aggregate returns r_{it} from portfolios and estimates (6.4). Portfolios are constructed as weighted averages (by AUM) of asset class investments per sponsor in a given year. The risk-adjusted return estimates only include U.S. plans and are only shown for stocks, fixed income, alternative, and total portfolio. Risk-adjusted returns are estimated at the asset class level instead of sub-asset class level. Robust standard errors are reported in parentheses and clustered by sponsor. Boldface coefficients are statistically significant at the 5% level. The "Panel reg." rows show the effect on policy-adjusted gross and net returns of moving from the bottom 10th percentile to the upper 90th percentile in plan size in 2019 based on the panel estimates in the upper panel. The "Portfolio sort" rows show the effect on policy-adjusted gross and net returns of moving from the bottom 30th percentile to the upper 70th percentile in plan size within a year. Portfolios are constructed as equal-weighted average returns of sub-asset classes within a year and for a given plan size.

		Stocks	Fixed income	Private equity	Private debt	Real assets	Alt.	All		Stocks	Fixed income	Real assets
Panel A: Cost (in bps)												
	Internal	**-2.97**	**-5.38**	**-320.00**	**-26.00**	**-47.06**	**-55.69**	**-4.28**	Passive	**-9.49**	**-1.97**	**-9.43**
		(0.567)	(1.054)	(65.806)	(8.598)	(14.945)	(11.006)	(1.574)		(0.509)	(0.385)	(0.860)
	External	**7.37**	**5.01**	**96.34**	**24.43**	**39.16**	**54.32**	**17.59**	Active	**14.70**	**4.88**	**16.12**
		(0.482)	(0.670)	(5.981)	(4.660)	(3.140)	(2.695)	(0.769)		(0.625)	(0.342)	(1.366)
	Treated units											
	Internal	212	186	36	11	99	145	545	Passive	720	298	44
	External	210	181	36	14	83	133	526	Active	551	260	28
	Obs	25184	19101	5609	1136	9808	16553	60839		25184	19101	9808
Panel B: Returns (in bps)												
Gross	Internal	**105.06**	**39.56**	**230.77**	-5.09	**197.60**	**192.89**	**89.47**	Passive	-24.19	4.54	36.67
		(23.734)	(13.770)	(109.327)	(64.413)	(65.048)	(51.383)	(17.420)		(19.824)	(13.871)	(41.692)
Net	Internal	**107.81**	**47.26**	**254.72**	32.50	**193.64**	**197.72**	**93.07**	Passive	-13.42	7.54	47.64
		(23.866)	(13.999)	(109.474)	(61.681)	(66.086)	(51.949)	(17.591)		(19.825)	(13.861)	(41.539)
	Treated units	202	157	30	8	95	133	494		687	279	39
Gross	External	**146.02**	**34.79**	**-523.39**	**-107.85**	-28.01	**-167.79**	**36.70**	Active	-21.53	-5.79	-17.42
		(21.293)	(15.751)	(122.537)	(47.167)	(53.532)	(46.874)	(16.338)		(16.290)	(14.958)	(49.319)
Net	External	**139.23**	25.84	**-578.24**	**-113.89**	-60.28	**-202.59**	22.03	Active	**-36.17**	-11.37	-34.82
		(21.296)	(15.686)	(122.262)	(47.779)	(53.931)	(47.025)	(16.371)		(16.307)	(14.956)	(49.285)
	Treated units	197	152	28	12	86	126	476		541	255	26
	Obs	24814	18700	5446	1078	9514	16039	59564		24814	18700	9514

Table 8: **Effect of asset management style on cost and returns using matching.** This table shows the effect of switching from external to internal management (Internal), internal to external management (External), active to passive management (Passive) and passive to active management (Active) on cost (Panel A) and policy-adjusted returns (Panel B) for different asset classes. The asset classes "Alt" and "All" pool observations across the alternative asset classes and all asset classes respectively. In Panel A, the effect is estimated using the following controls: AUM_{iat}, total AUM allocated by plan i to sub-asset class a at time t; Private_i, an indicator denoting whether plan i is private; nonUS_i, an indicator denoting whether plan i is domiciled in the U.S.; and sub-asset class a at time t to ensure that plans in the treated group are matched with plans in the control group that invest in the same sub-asset class. To estimate the effect of internal/external (passive/active) management, we also use the control: Active_{iat} (External_{iat}), an indicator denoting if plan i manages sub-asset class a actively (externally) at time t. In Panel B, the effect of management style is estimated separately for gross and net returns, using the controls: AUM_{iat-1}; and sub-asset class a at time t. Robust standard errors are reported in parentheses and boldface coefficients are significant at the 5% level. "Treated units" denotes the number of plans that switch management style by asset class.

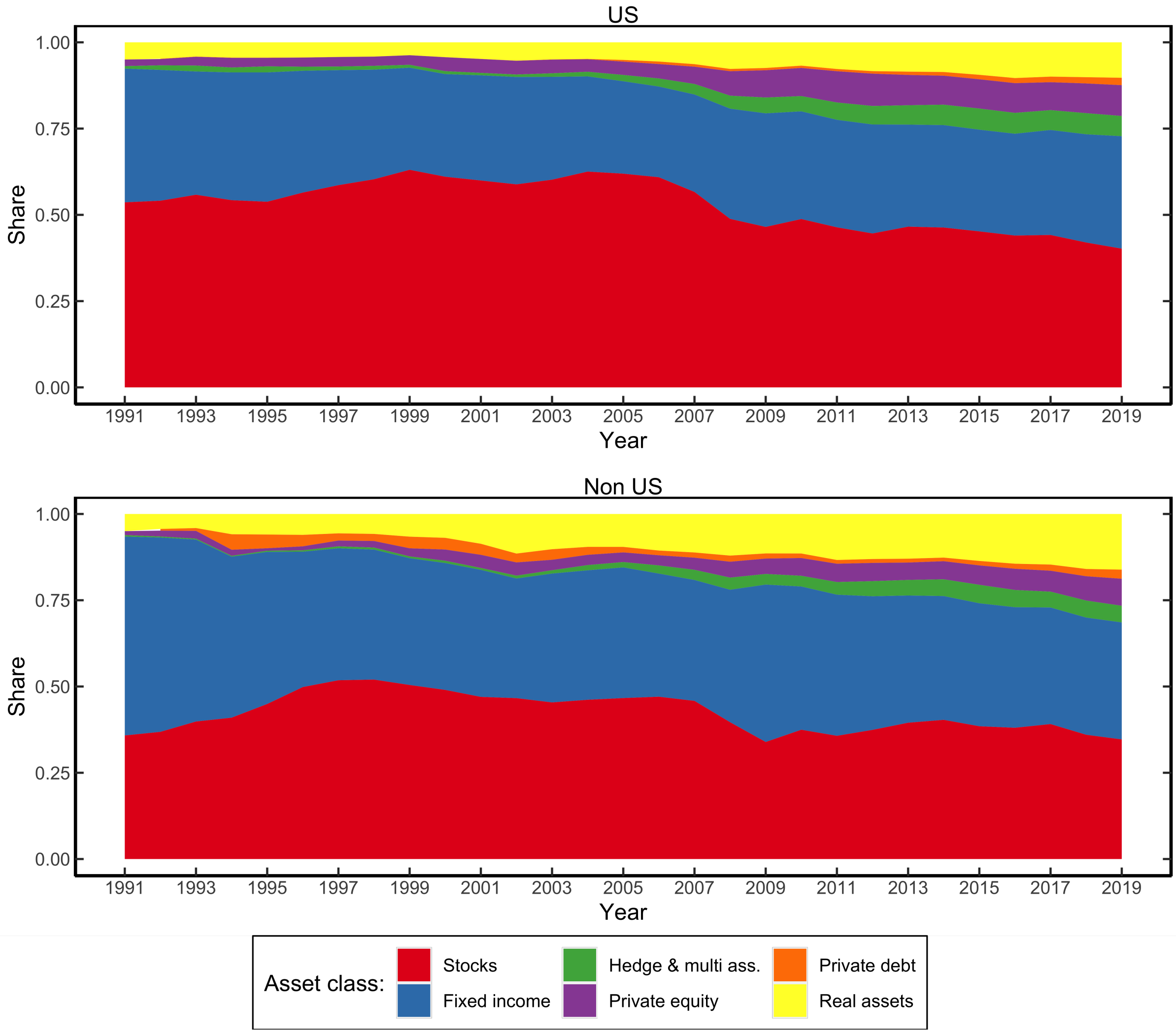


Figure 1: **Asset allocation over time**: This figure shows the share of total AUM allocated to each of the six asset classes within a year. The shares are reported separately for U.S. plans (top panel) and non-U.S. plans (bottom panel).

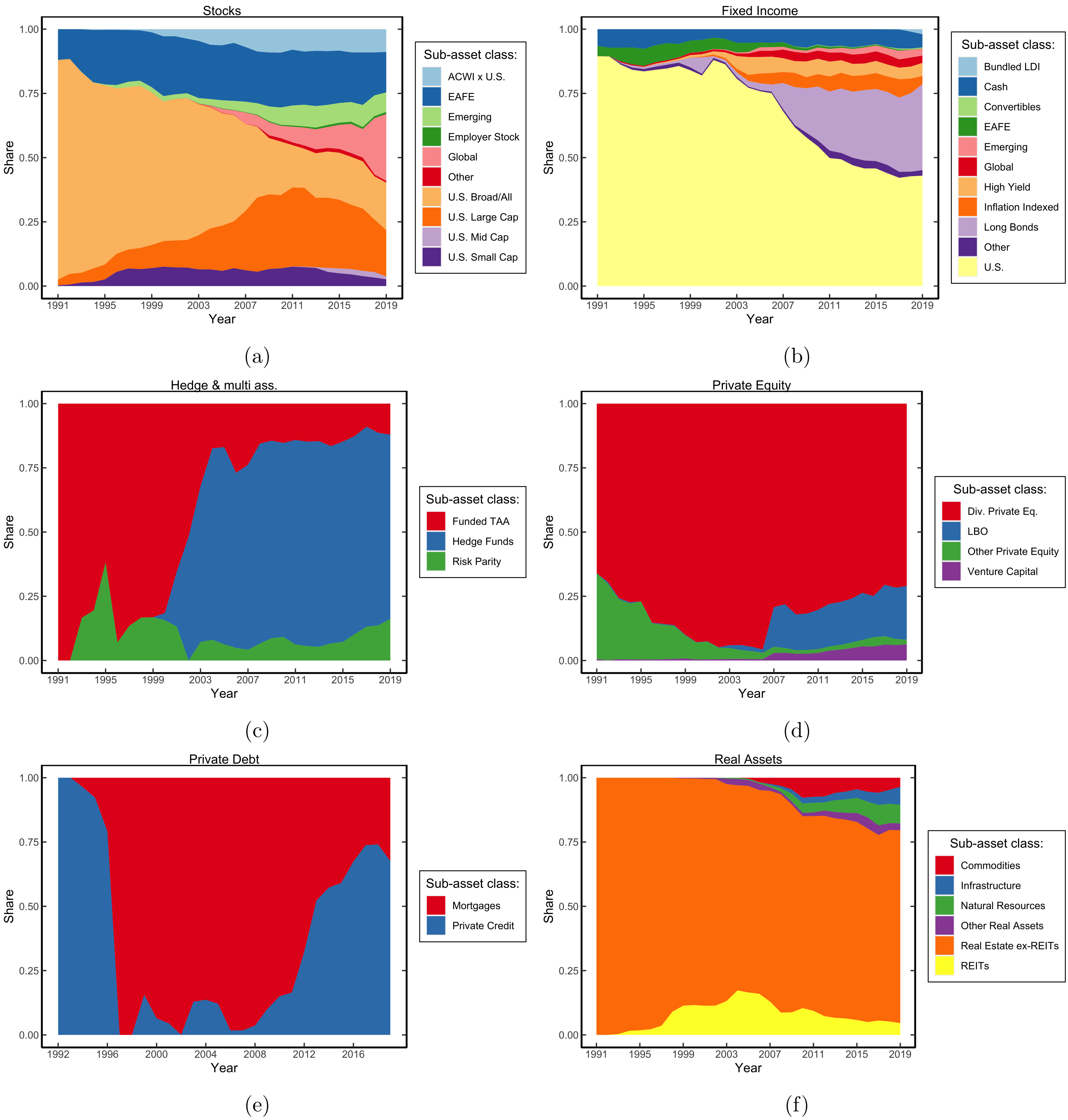


Figure 2: **Sub-asset class allocation over time for U.S. plans.** This figure shows the share of total AUM allocated to each sub-asset class for a given year and asset class for U.S. plans only.

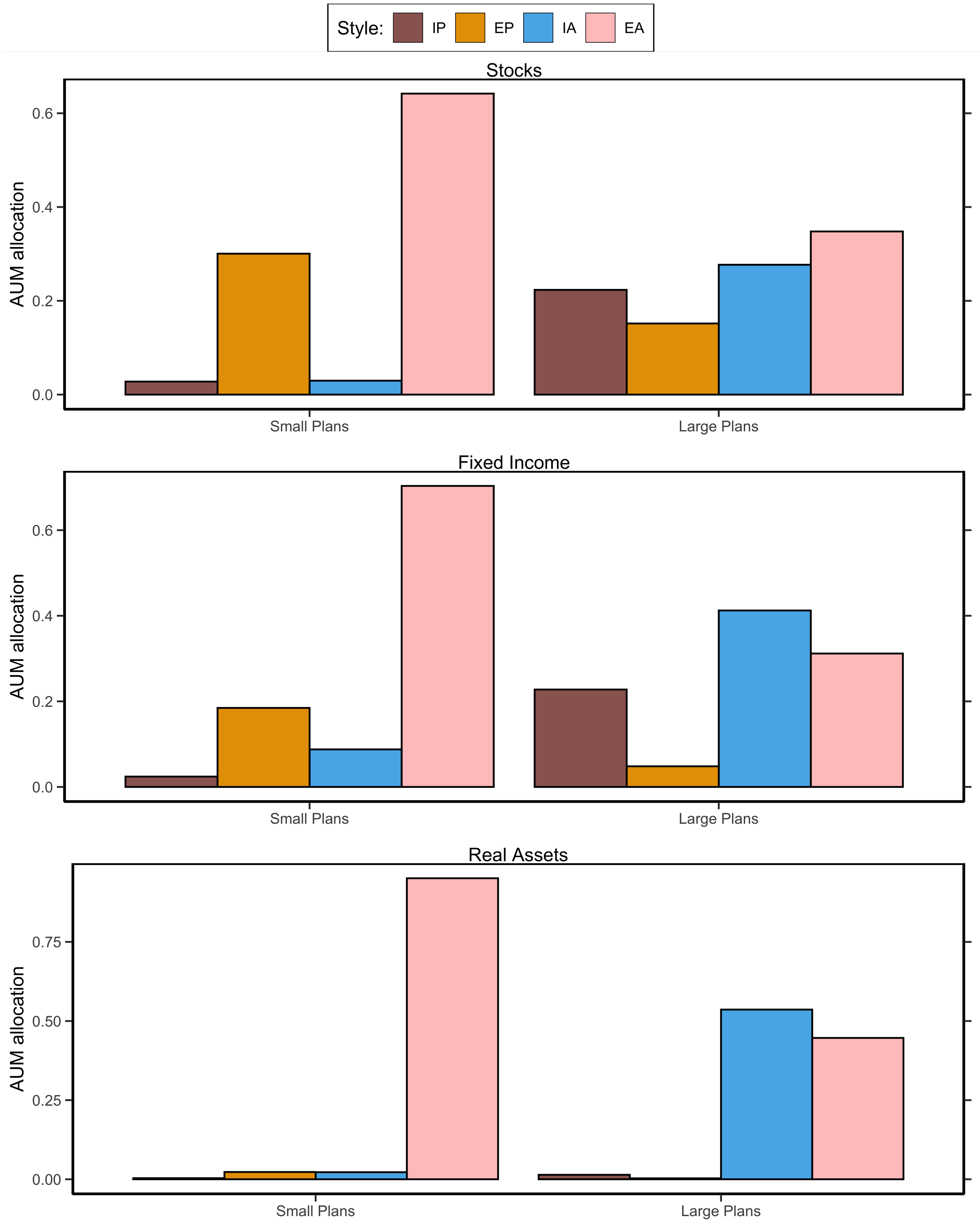


Figure 3: **Asset allocation by management style and plan size.** This figure shows the share of total AUM allocated to the four management styles: Internal Passive (IP), External Passive (EP), Internal Active (IA) and External Active (EA). The shares are calculated in 2019 for the asset classes: Stocks, Fixed Income and Real Assets. Within each year, we also distinguish by small and large plans, which are defined by the bottom 30 and top 70 percentile relative to the total AUM within an asset class.

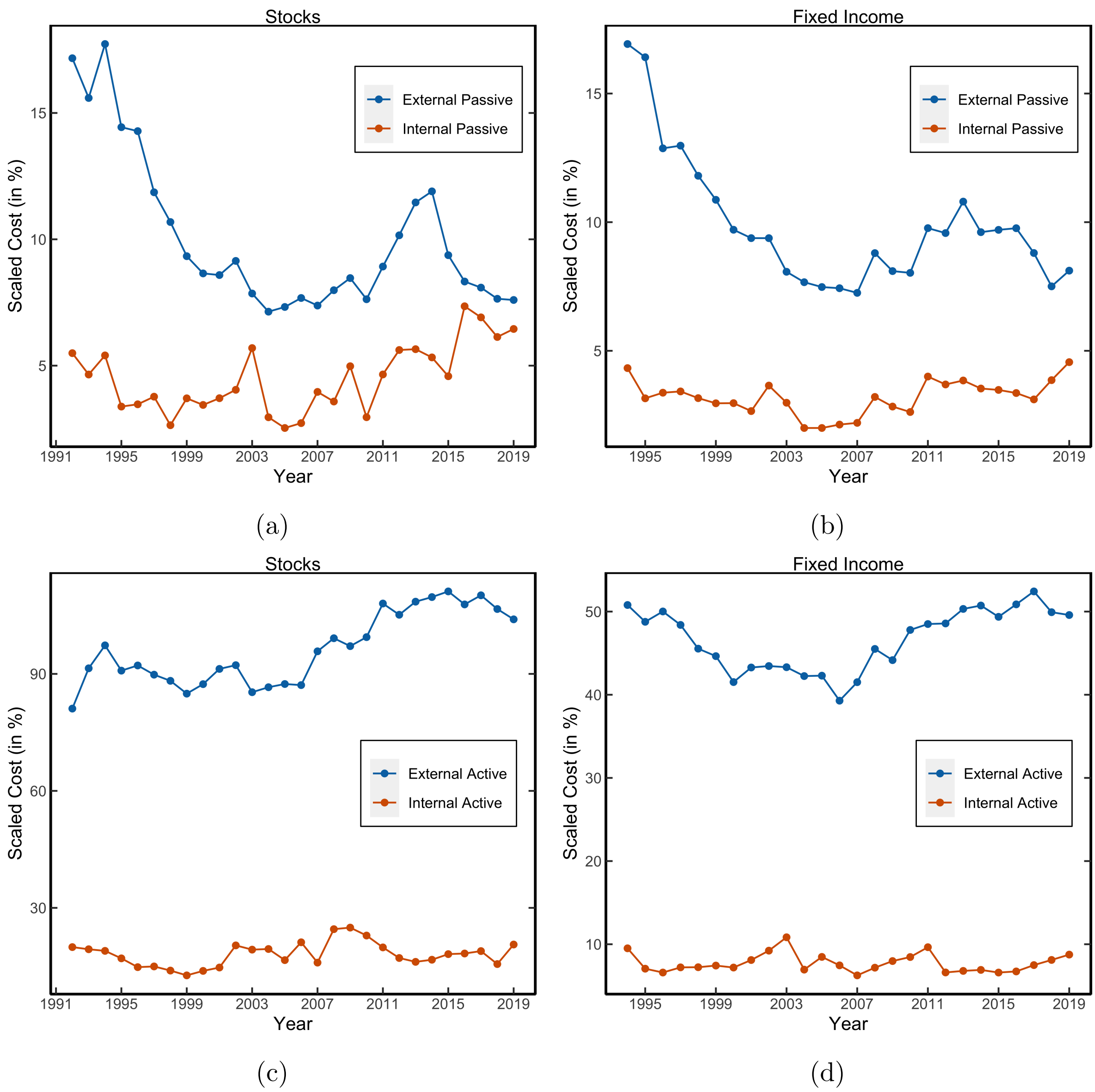
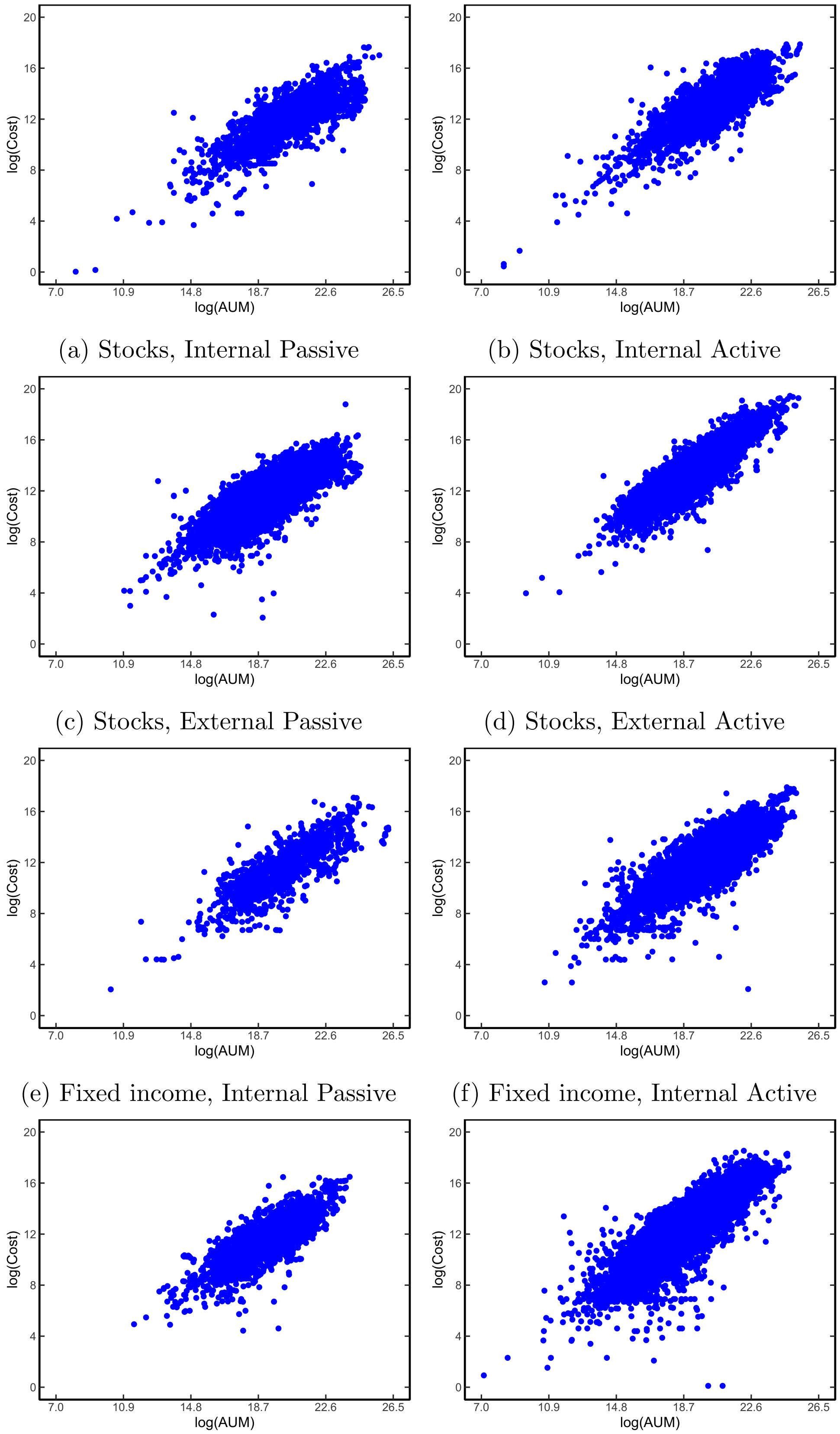


Figure 4: **Median cost by asset management style**. The figure shows a time series plot of the (scaled) median cost across plans by asset management style for the public asset classes. The four asset management styles considered are: Internal Passive, External Passive, Internal Active, and External Active management. We only include years that have enough plan observations for each asset class and style. Median cost are scaled by the average cost across years and plans.



(a) Stocks, Internal Passive

(b) Stocks, Internal Active

(c) Stocks, External Passive

(d) Stocks, External Active

(e) Fixed income, Internal Passive

(f) Fixed income, Internal Active

(g) Fixed income, External Passive

(h) Fixed income, External Active

Figure 5: **Relation between log Cost and log AUM**. This figure shows a scatter plot of $\log(\text{AUM}_{iats})$ versus $\log(\text{Cost}^{\$}_{iats})$, where AUM_{iats} (resp. $\text{Cost}^{\$}_{iats}$) denotes the dollar AUM holdings (resp. dollar cost) of plan i in sub-asset class a at time t for asset management style s. The asset management styles we consider are: Internal Passive, Internal Active, External Passive and External Active. In each panel and for a given style, observations are pooled across plans, sub-asset classes, and years over the sample period 1991–2019.