Asset managers: Institutional performance and factor exposures*

Joseph Gerakos Juhani T. Linnainmaa Adair Morse

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Abstract

Using data on $18 trillion of assets under management, we show that actively managed institutional accounts outperformed strategy benchmarks by 88 (44) basis points on a gross (net) basis during the period 2000–2012. Estimates from a Sharpe (1992) model imply that asset managers' outperformance came from factor exposures. If institutions had instead implemented mean-variance efficient portfolios using index and institutional mutual funds available during the sample period, they would not have earned higher Sharpe ratios. Our results are consistent with the average asset manager having skill, managers competing for institutional capital, and institutions engaging in costly search to identify skilled managers.

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1 Introduction

We estimate that, from 2000 to 2012, institutions delegated an average of $36 trillion per year to asset managers.[1] These asset managers primarily followed active strategies; hence, assets delegated by institutions represented, over our sample period, the majority of actively managed assets.[2] Institutions are sophisticated investors. If active investing is even approximately a negative sum game (Sharpe, 1991; Pedersen, 2018), why did institutions delegate these assets to active managers? In this study, we analyze the performance of these delegated assets and find that the answer to this question is straightforward. Institutions earned positive alphas on the assets that they delegated to active strategies. And, they would not have done better managing passive strategies in house.

Our results are consistent with the following characterization of the institutional side of the asset management industry. First, the average asset manager has skill, and this skill persists (Berk and Binsbergen, 2015). Second, managers offer fee discounts to compete for institutional capital. Managers and institutions therefore share the rents that asset managers extract from the rest of the market (Pástor and Stambaugh, 2012). Third, institutions appear to engage in costly search to find skilled managers. Asset managers with large clients display more skill than those with small clients. This result is consistent with large clients facing lower search costs relative to capital (Gârleanu and Pedersen, 2018). Fourth, the fact that asset managers offer the same fund at different fees implies that not all clients can earn an expected zero net alpha: even for the same fund, net alpha can be positive for some clients and negative for others (Berk and Green, 2004; Gârleanu and Pedersen, 2018).

A global consultant provided data covering an annual average of $18 trillion in institutional assets under management over the period 2000 to 2012. The database is free of

[1] This estimate is based on annual surveys by Pensions & Investments, which we describe in the appendix.

[2] Fender (2003) estimates that, in 2001, asset allocations for European institutions were 90% in active strategies for equity and 98% for fixed income, and for U.S. institutions they were 64% for equity and 87% for fixed income. Anadu et al. (2018) estimate that total assets in active mutual funds and ETFs were approximately $8 trillion in 2008.

survivorship bias and includes the dates on which funds were added to the database thereby allowing us to remove backfill bias.[3] The data include quarterly assets and client counts, monthly returns, and fee structures for 23,883 strategy-level funds marketed by 3,403 firms.

Our analysis focuses on four broad asset classes included in the database: U.S. fixed income, global fixed income, U.S. public equity, and global public equity. When we benchmark each fund against the performance of its broad asset class, we find an annual gross alpha of 134 basis points (t-value = 3.26). Under the assumption that the Consultant's data are representative of institutional delegation in general, the 134 basis point gross alpha, combined with the adding-up constraint discussed by Sharpe (1991), implies that the market-adjusted gross alpha for all other investors is -55 basis points.

Because institutions typically evaluate the performance of delegated assets relative to strategy-specific benchmarks, these results do not necessarily imply that institutions view delegated assets as earning positive risk-adjusted returns. We therefore estimate alphas relative to strategy-level benchmarks while allowing betas to vary. We find that the average fund earns an annual strategy-level gross alpha of 88 basis with a t-value of 3.35 and net alphas range from 32 to 55 basis points depending on client size. To further evaluate performance, we calculate the Berk and Binsbergen (2015) measure of manager value added. Using this measure, we find that institutional asset managers appear to have skill: value adds are persistent, less than half the funds have negative value adds, and a manager that displays skill in one fund likely displays skill in its other funds in other asset classes

How did asset managers achieve these positive gross alphas? We use the Sharpe (1992) approach to construct long-only portfolios of indices that best mimic each fund. We find that funds do not outperform these mimicking portfolios. The fact that asset managers out-

[3] Asset managers are subject to Global Investment Performance Standards (GIPS®) that require consistent and reliable reporting of performance. We discuss the implications of these standards on selection bias and backfill bias in Section 2. See, also, Caccese and Lim (2005). The mandatory public disclosure requirements of The Investment Company Act of 1940 cover funds offered to retail investors, but not capital delegated by institutions.

perform strategy-level benchmarks but earn returns comparable to the fund-level mimicking portfolios implies that asset managers provide institutional clients with profitable systematic deviations from benchmarks. We further show that if institutions had instead implemented mean-variance efficient portfolios using index funds and institutional mutual funds available during the sample period, they would not have earned higher Sharpe ratios.

An important open question in the literature is what is the division of market power between managers and investors. Berk and Green (2004) combine decreasing returns to scale at the manager level with perfect competition among investors. In their model, a skilled manager extracts all rents. Because they assume that the investor side of the market is perfectly competitive, investors always earn zero net alphas in expectation. Pástor and Stambaugh (2012) and Pedersen (2015) instead assume that returns decrease in scale at the market level and allow investors to have market power. Our results suggest that both sides have market power. The 134 basis point gross alpha translates to $480 billion per year, with $318 billion accruing to institutions and $162 billion to asset managers. Asset managers' fee schedules also indicate that asset managers share rents with investors. In U.S. equities, for example, the typical fee for the first dollar invested is 77 basis points; for a $10 million allocation, it is 68 basis points; and for a $100 million allocation, it is 54 basis points. That is, clients have negotiation power and asset managers, facing competition, cannot keep all the rents by giving take-it-or-leave-it offers.

Our results are in contrast with studies that examine the aggregate performance of institutions. For example, Lewellen (2011) uses 13-F filings to study the performance of total institutional holdings (that is, delegated capital and capital managed in house) in U.S. public equity and finds that institutions do not outperform benchmarks. Our results, combined with those of Lewellen (2011), imply that capital managed in house likely underperforms delegated capital.

We are not the first to examine the delegation of institutional assets. Jenkinson et al. (2016) find that consultants' investment recommendations do not add value for institutions already investing in U.S. actively managed equity funds. Similarly, Goyal and Wahal (2008) find that, when pension fund sponsors replace asset managers, their future returns are no different from the returns that they would have earned had they stayed with the fired asset managers. These studies examine cross-sectional variation in performance, and find that consultants do not recommend managers who go on to deliver superior returns. Our result is that even the average manager already outperforms the market.

Our results about market efficiency and the asset management industry are consistent with Grossman and Stiglitz (1980) and Pedersen (2015). Prices do not appear to be fully efficient (Fama, 1970), but, rather, appear to exhibit an "equilibrium degree of disequilibrium" (Grossman and Stiglitz, 1980, p. 393). Institutional asset managers, as a group, profit from those informational inefficiencies. However, instead of trading directly on their information with their own capital, asset managers, in effect, sell this information to their clients for a fee (Admati and Pfleiderer, 1990). Indeed, we find that asset managers charge higher fees in those market segments that appear to be informationally less efficient. Information acquisition costs, competition among asset managers, and costly search sustain some price efficiencies and result in an industry in which asset managers divide the rents with their clients.

2 Data and descriptive statistics

Consultants to institutional investors often build and maintain databases of asset manager performance. These databases contain quarterly assets under management and number of clients, current fee structures and strategy descriptions, and monthly performance for the strategies that they offer clients. Asset managers voluntarily report data to consultants because, in essence, the consultants are the asset managers' primary clients. The majority of institutional investors use consultants to construct portfolios (Goyal and Wahal, 2008;

Jenkinson et al., 2016).[4]

We obtained such a database from a large global consulting firm (the "Consultant").[5] Because the Consultant's business model depends on data reliability, it employs a staff of over 100 researchers who perform regular audits of each asset manager and its funds. In the course of these audits, the researchers evaluate the fund's strategy benchmark and verify the accuracy of the performance and holdings data. When evaluating funds, the Consultant and its clients can read these audits, compare the fund to strategy benchmarks, and review the credentials of the fund's managers. Asset managers who do not self-report performance to the Consultant may receive less attention when the Consultant makes recommendations to its clients. Moreover, the Consultant and its clients may interpret non-reporting as a negative signal of fund quality.

Asset managers hold institutional capital in individual accounts or in accounts that pool small numbers of institutions. When asset managers report institutional holdings and performance to consultant databases, they either identify one account as being representative of the strategy's performance or create a composite account by adding up all of the clients within the same strategy.[6] These vehicles represent our unit of analysis and we refer to them as "asset manager funds" to draw a parallel with mutual funds.

[4] Goyal and Wahal (2008) estimate that, in the U.S., 82% of local public pension plans, 68% of state pension plans, 58% of endowments and foundations, 67% of union pension plans, 64% of public universities, 61% of private universities, and 50% of corporate pension plans use investment consultants. Jenkinson et al. (2016) describe the services that consultants provide institutional investors. In Table A1 of the appendix, we present estimates of total consultants' total worldwide and total U.S. institutional assets under advisement for our sample period. These estimates are based on annual surveys implemented by Pensions & Investments. Total worldwide institutional assets under advisement grew from $13 trillion in 2004 to over $31 trillion in 2012.

[5] In the Pensions & Investments surveys, this Consultant was consistently ranked as one of the largest consultants with respect to total institutional assets under advisement.

[6] The pooled strategy-level vehicle is also the unit used by asset managers to comply with GIPS® reporting standards. What is now the CFA Institute, initiated GIPS® in 1987 to ensure minimum acceptable reporting standards for investment managers. In 2005, GIPS® became the global standard. Compliance is voluntary, but asset managers have almost universally adopted GIPS®.

2.1 Aggregate assets under management

The first column of Table 1 reports our estimates of worldwide investable assets for each year between 2000 and 2012. These estimates include real estate, government bonds, bonds issued by financial institutions, corporate bonds, private equity investments, and public equity.[7] Worldwide investable assets start at $79 trillion in 2000 and grow to $173 trillion in 2012. They increase every year except for a major drop in 2008 (from $157 trillion to $135 trillion) and a minor drop in 2011 (from $165 trillion to $163 trillion). Over the sample period, average annual worldwide investable assets are $125 trillion.

The second column presents aggregate institutional assets under management for each year between 2000 and 2012. These estimates are based on the annual Pensions & Investments surveys, which we describe in the appendix.[8] Total institutional assets increased from $22 trillion in 2000 to $47 trillion in 2012. The third column shows that institutional assets held by asset managers remained relatively constant over the sample period at approximately 29% of worldwide investable assets.

We next compare the coverage of the Consultant's database with the Pensions & Investments data. The fourth column reports assets under management covered in the Consultant's database. They start at almost $7 trillion in 2000 and rise to $28 trillion in 2012. Column 5 presents the Consultant's assets under management as a percentage of aggregate institutional assets according to Pensions & Investments. The Consultant's total assets cover 31% of institutional assets under management in 2000, and rise to over 60% after 2006.

Our data cover approximately half of the assets that institutions delegate to asset managers. When we hand match the names of the asset manager firms in the Consultant's database with those in the Pensions & Investments, 82.6% of the firms in Pensions & Invest-

[7] In Table A2 of the appendix, we describe how we generate these estimates and provide annual breakdowns by asset class.

[8] Each year, Pensions & Investments conducts several surveys of asset managers about their assets under management. These surveys are important to asset managers because they provide size rankings to potential clients. According to Pensions & Investments, nearly all medium and large asset managers participate.

ments are included in the Consultant's database. We examined the missing firms and found that nearly half of these firms are private wealth managers or smaller insurance companies. Another 16% of the missing firms specialize in private equity, real estate, or other alternative assets, which represent asset classes that we do not consider in our analysis. The remaining missing firms consist of retail banks mostly from Italy and Spain, and boutique asset managers from the U.S., which presumably cater to specific clients and thus do not advertise. We therefore believe that we have close to the population of large asset managers worldwide that serve institutional clients, except for perhaps asset managers located in southern Europe.

We next consider the possibility of selective reporting by the asset managers included in the Consultant's database. It could be (i) that asset managers always exclude certain clients' accounts, (ii) that asset managers selectively report assets under management and returns when returns are good, or (iii) that they report assets under management but not the returns when performance is good. Based on discussions with the Consultant, we infer that (i) accounts for most of the missing fund-level data. In particular, the Consultant disclosed that missing from the database are specialized proprietary accounts. When choosing asset managers, institutional investors can only see funds that appear in the databases. Thus, although the data are incomplete, they nonetheless represent an institutional investor's information set for deciding among funds that are open for investment.[9]

Regarding issues (ii) and (iii), asset managers cannot selectively report based on performance and be in compliance with GIPS® reporting procedures, which require firms "to include all actual, discretionary, fee-paying portfolios in at least one composite defined by investment mandate, objective, or strategy to prevent firms from cherry-picking their best performance." This constraint especially binds starting in 2006, when GIPS® was revised and became the global reporting standard for asset managers. In robustness tests, we split the sample at 2006 to ensure that our inferences hold in the recent period.

[9] Ang et al. (2018) make a similar point with respect to endowments making allocation decisions regarding alternative asset classes.

Two related concerns are survivorship and backfill biases. Survivorship bias may occur if funds that closed were removed from the database. However, this is not the case—the Consultant leaves dead funds in the database. Regarding backfill, the Consultant records a "creation date" for each fund, reflecting the date that the fund was first entered into the system. At the initiation of coverage, the manager can provide historical returns for the fund. Such backfilled returns would be biased upward if better performing funds were more likely to survive and/or provide historical returns. In our analysis, we only include returns generated after the fund's creation date. In the second to last column of Table 1, we present the total assets management with returns that were generated after the creation date, which range from $3.3 trillion in 2000 to $24.6 trillion in 2012.

Industry professionals view databases such as the one provided by the Consultant to be of research quality. Institutions care about data quality and consultants, in turn, have incentives to construct and maintain unbiased databases. To see why, consider the objectives of academic researchers and institutions. Mutual fund researchers, for example, care about data quality because various biases, such as backfilling and survivorship biases, can significantly alter inferences about fund performance. Institutions who seek to allocate their capital care about data quality for the same reason: if the data are not free of biases, their inferences about managers' abilities may be biased. Such biased inferences, in turn, could distort institutions' capital allocation decisions. Institutions rely on consultants to provide investment-quality databases, much in the same way as researchers rely on academic data providers to provide research-quality databases.

2.2 Aggregate fees

The Consultant's database includes the fee structure for each fund. For example, one U.S. fixed income-long duration fund charges 40 basis points for investments up to $10 million, 30 basis points for investments between $10 million and $25 million, 25 basis points for investments between $25 million and $50 million, and 20 basis points for investments above $50 million. The database records the latest fee schedule for all the funds provided by the manager.

We calculate three different estimates of aggregate fees. First, we calculate a *schedule middle point* estimate that assumes that the average dollar in each fund pays the median fee listed on the fund's fee schedule. This fee estimate could, however, be too high. Institutional investors could negotiate side deals that shift their placement in the fee schedule up. Second, we calculate a *schedule lower bound* estimate, which uses the lowest fee in the schedule for all capital invested in the fund. In the example above, we would apply the rate 20 basis points to all capital invested in the fund. This estimate does not account for the possibility that large investors might pay even less than 20 basis points. Such instances, however, are likely limited to select clients. Nonetheless, we implement a more conservative estimate that we call the *implied realized fee*. Some funds in the Consultant's database report both net and gross returns. These funds, which represent, on average, 20.1% of the total assets under management in our sample, therefore provide an estimate of effective fees. We annualize the monthly gross versus net return difference, take the value-weighted average, and then re-weight the asset classes so that the weight of each asset class matches that in the entire database.

Figure 1 plots annual estimates of aggregate fees received by asset managers for the three measures, aggregated to the total worldwide investable assets. We aggregate by taking the weighted average fees in the Consultant's database and then multiplying them by the estimates of worldwide delegated institutional assets under management from Pensions & Investments. Based on this aggregation, we estimate that average annual fees received by the top global asset managers over our sample period range from $125 billion based on *schedule lower bound* to $162 billion for *schedule middle point*. *Implied realized fee* in Figure 1 is close to the estimate based on the *schedule middle point*. This similarity suggests that asset managers set their fee schedules so that their typical client is located toward the middle of the schedule.

2.3 Fund-level assets under management

The Consultant categorizes funds into eight broad asset classes: U.S. public equity, global public equity, U.S. fixed income, global fixed income, hedge funds, asset blends, cash, and other alternatives. Our database starts with 23,883 funds and 3,403 asset manager firms over the 2000–2012 period. We drop hedge funds, asset blend funds, and other alternative funds, because these funds represent heterogeneous investment strategies that make benchmarking challenging. We also drop the cash asset class because these short-term allocations play a liquidity, rather than investment, role in portfolios.

After removing funds with no returns, cash funds, asset blend funds, other alternatives funds, hedge funds, funds with only backfilled returns, and funds that were inactive during the entire sample period, the sample consists of 16,130 funds across 2,194 asset manager firms. Table 2 reports descriptive statistics for this sample. For completeness, at the bottom of each panel, we include descriptive statistics for the asset classes that we drop.

Panel A reports that the average total assets under management in the sample is $9.7 trillion. In terms of age, the funds in the database are relatively established with the average fund being 12 years old. The largest asset classes are global and U.S. public equity with, on average, $2.7 trillion and $2.8 trillion in assets under management followed by U.S. fixed income ($2.3 trillion) and global fixed income ($1.8 trillion).

Panel B reports descriptive statistics at the fund level. For each month, we calculate the distributions and then take the average of the distributions. The average fund has $1.9 billion in assets under management, and the median fund has $419 million. The skew is due to large institutional mutual funds in the database. Hence, we focus on median statistics. The median fund has 6.5 clients and $55.3 million assets under management per client. Many institutional investors have much smaller allocations (or “mandates”). The 25th percentile mandate is just under $13 million.

We next present fund-level descriptive statistics for the four broad asset classes. The largest funds are U.S. and global fixed income, which have, on average, $2.7 billion and $2.2 billion in total assets under management as of 2012, followed by global public equity ($1.7 billion) and U.S. public equity ($1.5 billion).

Panel C reports descriptive statistics for fund-level performance and the performance of asset-level and strategy-level benchmarks. We report average returns, standard deviations, and Sharpe ratios.[10] Across the four asset classes in the main sample, funds earn average returns and Sharpe ratios that exceed the asset-class and strategy benchmarks.

2.4 Fund-level fees

We next examine fee distributions by asset class and client size. Table 3 shows that the average delegated institutional dollar pays a fee of 44 basis points. This estimate is based on the *schedule middle point estimate* presented in Figure 1, which aggregates up to $162 billion if applied to our estimate of total delegated institutional assets. The value-weighted mean fee is lowest for U.S. fixed income (28.7 basis points), followed by global fixed income (31.9 basis points), U.S. public equity (49.2 basis points) and global public equity (58.2). Fees in the global asset classes are more right-skewed and therefore have higher means.

Our fee estimates are in line with those reported in both the press and academic research. For example, Zweig (2015) reports that CalPERS paid an average fee of 48 basis points in 2012. Coles et al. (2000) describe the fee price breaks for closed-end institutional funds. They

[10]In our analysis of the four asset classes in the main sample, we use the following broad asset class benchmarks: Russell 3000 (U.S. public equity), MSCI World ex U.S. Index (global public equity), Barclays Capital U.S. Aggregate Index (U.S. fixed income), and Barclays Capital Multiverse ex US Index (global fixed income). Table A4 provides return statistics for the benchmarks and the Consultant's funds mapped to each asset class. The broad asset classes for three of the excluded asset classes are 60% $\times$ MSCI World + 40% Barclays Capital Global Aggregate (asset blends), Merrill Lynch/Bank of America Treasury 1-3 Years (cash), and HFRX Absolute Return (hedge funds). Given the heterogeneity in the fourth excluded asset class (other), we do not specify a benchmark.

find that a typical fund charges 50 basis points for the first $150 million, 45 basis points for the next $100 million, 40 basis points for the subsequent $100 million, and 35 basis points allocations above $350 million. Examining active U.S. equity institutional funds, Busse et al. (2010) find that fees are approximately 80 basis points for investments of $10 million and approximately 60 basis points for investments of $100 million.

Most asset managers use tiered fee schedules in which the fee depends on the amount of assets that the client allocates to the fund. In the Consultant's database, 93.2% of the funds use tiered fee structures. The most common fee schedule has three tiers, but some funds have up to eight tiers. In Figure 2, we report the average fee applied to an investment in excess of the amount indicated on the x-axis. If a single fund is offered to clients through multiple vehicles, we compute an equal-weighted average over the vehicles to get a fund-level fee schedule. The fee schedules in Figure 2 are equal-weighted averages of the schedules of all funds in each asset class.

In all asset classes, large investments typically pay significantly lower fees than small investments. In U.S. public equity, for example, the first dollar pays an average fee of 77.3 basis points.[11] An investment in excess of $10 million pays a fee of 67.9 basis points, and an investment in excess of $100 million a fee of 53.8 basis points. Although some funds offer fee discounts at even higher levels, the fee schedules flatten after the $100 million threshold. Moving from an investment of $1 dollar to over $100 million, the average breaks in fees are 24 basis points (U.S. public equity), 15.9 basis points (global public equity), 13.5 basis points (U.S. fixed income), and 8.8 basis points (global fixed income).

Tiered fee schedules are an important feature of the institutional asset management industry. By contrast, retail mutual funds typically charge all investors the same fee.[12] The

[11] In addition to the fee schedules, funds also sometimes impose minimum fees. If an investment is very small, the effective fee can be higher than the highest fee on the fee schedule because of these minimum fees. In Figure 2, we do not take these minimum fees into account.

[12] There are exceptions. Effective fees can vary because some funds are offered with either front- or back-end loads, and some funds have multiple share classes with different expense ratios. Employers can also offer share classes with lower expense ratios through 401(k) and 403(b) plans, because mutual fund companies

existence of these tiered fee schedules, by itself, rejects the Berk and Green (2004) model. The key prediction of this model is that every investor expects to earn a zero alpha after fees. An investor who expects a positive alpha net of fees should allocate more assets to the fund. In the institutional setting, this mechanism fails due to tiered fees. Because different investors pay different fees, some investors must earn positive and others negative net alphas even if the average net alpha is zero. Other models of the asset management industry, such as Gârleanu and Pedersen (2018), model fees as fixed dollar amounts, which means that, as in the data, the fees paid by large institutions are lower than those paid by small institutions.

3 Performance

We compare fund performance against four sets of benchmarks: broad asset class benchmarks, strategy-specific benchmarks, a matched sample of mutual funds, and mimicking portfolios that combine indices specific to each asset class. These benchmarks serve different purposes. The comparison with the performance of the broad asset classes (for example, how funds that invest in U.S. equities perform relative to the entire U.S. equity market) is informative about aggregate wealth transfers to and from institutional investors and asset managers. The comparison with strategy-specific benchmarks represents performance from the perspective of institutional investors. Institutions typically focus on performance relative to the strategy-level benchmark, because they first choose the strategy and then, typically with the help of a consultant (Goyal and Wahal, 2008), pick the manager to provide a vehicle inside that strategy. The comparison with mutual funds informs academic research, because a large portion of the academic literature treats mutual funds as representing the universe of active investors. We compare performance with mimicking portfolios to measure the extent to which asset manager funds outperform and, if so, identify the source of outperformance.

sometimes offer funds with lower fees when the number of clients in the plan is large.

3.1 Asset class-benchmarked performance

We first evaluate performance relative to broad asset class benchmarks by regressing monthly fund returns in excess of the one-month Treasury bill on the excess return of each broad asset class benchmark. We estimate these regressions separately for funds' gross and net returns, and report annualized alphas and tracking errors. Panel A of Table 4 reports that the overall (column 1) beta is less than one (0.93). The average delegated institutional dollar earns a gross alpha of 191 basis points (t-value = 3.95).

What are asset manager funds net alphas in this analysis? Because of the use of tiered fee structures (see Figure 2), asset manager funds typically do not have a single net alpha. We report three net alphas to capture the dependency between net alphas and client size. Small institution in our analysis is a client that always pays the highest fee on the fund's fee schedule; medium-sized institution pays the median fee, which is the *schedule middle point* in Figure 1; and large institution pays the lowest fee, which is the *schedule lower bound* in Figure 1.[13] We find that small institutions earn a net alpha of 135 basis points (t-value = 2.78); medium-sized institutions an alpha of 148 basis points (t-value = 3.04); and large institutions an alpha of 158 basis points (t-value = 3.25).

In the second column, we report value-weighted returns over broad asset-class benchmarks by constraining the betas to one. The estimates we report here therefore represent *market-adjusted returns*. We find that the average dollar has a market-adjusted gross alpha of 134 basis points with a t-value of 3.26. The net alphas of institutions increase from 78 to 100 basis points, and the t-values from 1.88 to 2.43, when we move from small to large

[13] Because client net returns depend on the fees that the client pays, asset managers typically report gross returns to the consultant. On an assets-under-management basis, 84.8% of funds report gross returns; 35.9% of funds report net returns; and 20.6% report both. We compute gross and net returns as follows. We define gross return as the reported gross return if available and, if not, as the net return plus the median fee on the fee schedule. We define the net return of a medium-sized institution as the reported net return if available and, if not, as the gross return minus the median fee on the fee schedule. We then define the net returns of small and large institutions by lowering or increasing this net return by the differences between the median fee and the highest and lowest fees on the fund's fee schedule.

institutions.

Asset manager funds' positive gross alphas imply, through the adding-up constraint argument of Sharpe (1991), that the rest of the market earns negative gross alphas relative to the market. Our sample encompasses over 11% of the total worldwide investable assets. If we assume that these data are representative of the aggregate delegated institutional capital in the Pensions & Investments surveys, we can extrapolate our estimates to approximately 29% of worldwide investable assets. The market clearing constraint implies that if the funds that serve institutions outperform the index by 134 basis points before fees, everyone else must underperform by 55 basis points.[14] "Everyone else" in this computation is the sum of retail investors, retail mutual funds, and non-delegated investments of institutions; it is these investors that collectively earn lower returns in each asset class relative to institutional asset managers.[15]

The market-clearing constraint is uncontroversial: net gains from trade add up to zero. The "arithmetic of active management" extension of this argument by Sharpe (1991) is, however, controversial. He argues that the adding-up constraint implies that active and passive investors must earn identical gross returns. Pedersen (2018) and Berk and Binsbergen (2015, p. 5), however, note that the "market" itself changes over time because new companies and shares are added, old shares are repurchased, and companies sometimes delist. Hence, passive investors also need to trade to track the market. Passive investors, in turn, may then lose to active investors if they trade at prices that are systematically less favorable than those obtained by active investors.

[14] The market clearing constraint is that the average investor holds the market, which implies that $w_{\text{asset managers}}\hat{\alpha}_{\text{asset managers}} + (1 - w_{\text{asset managers}})\hat{\alpha}_{\text{everyone else}} \equiv 0$. We obtain the estimate of $\hat{\alpha}_{\text{everyone else}} = -55$ basis points from this condition.

[15] "Everyone else" may also include those institutional asset managers who do not provide information to the Consultant. Although the Consultant's data appear representative, we cannot rule out the possibility that non-reporting institutions systematically underperform those who report. If so, this selection mechanism—that funds who go on to underperform choose, ex ante, not to engage consultants—would warrant further study. The decision not to report, and its interaction with skill, could provide insights into the importance of the search mechanisms between institutions, consultants, and asset managers (Gârleanu and Pedersen, 2018).

In terms of institutional asset managers, the arithmetic of active management argument runs into an additional issue. Passive vehicles do not exist for all asset classes in which asset managers operate. The other asset class in the Consultant's database consists largely of private assets (e.g., real estate, venture capital funds, and private equity funds) that are difficult to hold directly in passive portfolios. Within this asset class, which we drop from our analysis because of the related benchmarking issues, the arithmetic of active management argument cannot hold (Pedersen, 2018, p. 25).

Maintaining the assumption that the Consultant's database is representative of the Pensions & Investments sample, the gross alpha estimate of 134 basis points implies that funds collectively earn \$480 billion per year from the rest of the market. If we use the *schedule middle point* for fees, then \$162 billion accrues to asset managers and \$318 billion accrues to institutions. Fama and French (2010) find that retail mutual funds' gross alphas are close to zero. If so, our results suggest that asset managers earn positive alphas at the expense of mutual funds, individual investors and non-delegated institutional investors. Berk and Binsbergen (2015) find, in contrast to Fama and French (2010), that "active mutual funds add value." If so, then even larger losses must accrue to individuals and non-delegated institutional investors.[16]

Asset managers' gross alphas are highest for Global fixed income (436 basis points with t-value of 4.94) and the lowest for U.S. public equity (96 basis points with a t-value of 1.90). How do these estimates for U.S. public equity compare with the estimates from prior studies? Using aggregate institutional holdings of U.S. public equities taken from 13-F filings,

[16] Fama and French (2010) estimate that the value-weighted average gross CAPM alpha of domestic mutual funds is -18 basis points (t-value $= -0.49$). Berk and Binsbergen (2015) do not report gross alphas but, instead, report gross alphas multiplied by assets under management. They find, when benchmarking funds against a combination of Vanguard index funds, that the average mutual fund added an average of \$250,000 per month in value. The difference between Berk and Binsbergen (2015) and Fama and French (2010) appears to emanate from differences in samples. Fama and French (2010) only consider pure-U.S. equity funds, while Berk and Binsbergen (2015) also include domestic funds that hold some international stocks. They note that "the fraction of AUM managed by funds that exclusively hold domestic stocks has dropped from 45% in 1977 to just 23% in 2011."

Lewellen (2011) finds an insignificant gross CAPM alpha of 32 basis points. For U.S. equity funds, Busse et al. (2010) estimate a gross alpha of 64 basis points per year. Similar to their results, we find that U.S. public equity has the lowest alpha. Lewellen's lower estimate may be due to poor performance of the non-delegated holdings of institutions, that are not included in our sample or in that of Busse et al. (2010).

3.2 Strategy-benchmarked performance

Institutions typically construct their portfolios through a two-step process.[17] They first determine their strategy-level allocations by optimizing over strategy-level risk and return. Investment officers then fulfill strategy allocations either in house or by issuing an investment mandate to an external manager. Because of this two-step process, institutions generally evaluate fund performance relative to a strategy benchmark.

The Consultant's database classifies the 16,130 funds into 171 strategy classes. "Australian equities," for example, is a strategy class under the broad asset class of global public equity. In addition, the database includes a benchmark for each fund. Prior to the Consultant entering a fund into the database, the manager recommends a benchmark. The Consultant then audits the fund's investment strategy to ensure that the recommended benchmark is appropriate. The Consultant enters a fund in the database only if the Consultant and manager agree on the appropriate benchmark.

For our sample of 16,130 funds, the database includes 7,149 unique fund-level benchmarks, many of which are combinations of indices or are not included on standard financial databases.[18] We therefore use one benchmark to evaluate the performance of all funds within each strategy. To determine the strategy-level benchmark, we start with the most commonly used benchmark within each strategy class. If the most commonly used benchmark is used

[17] For discussions of this process, see Goyal and Wahal (2008) and Jenkinson et al. (2016).

[18] Unusual fund-level benchmarks include, for example, (a) 25% × MSCI Brazil Index + 25% × MSCI Russia Index + 25% × MSCI India Index + 25% × MSCI China Index; (b) the Consumer Price Index plus 3%; and (c) the Brazilian Interbank Interest Rate.

by less than 10% of the funds in the strategy, we instead use the benchmark that covers the most assets under management.[19]

Panel B of Table 4 reports estimates from strategy-level single-factor models. We find a gross alpha of 88 basis points (t-value = 3.45) and net alphas that range from 32 (t-value = 1.24) for small institutions to 55 basis points (t-value = 2.13) for large institutions. In this estimation, the precision of benchmarking improves materially, especially in the global asset classes. The model's explanatory power increases from 70.0% (Panel A) to 82.3% (Panel B) when we replace broad asset class benchmarks with strategy-level benchmarks. Tracking error falls to 5.6%, which is almost identical to the Del Guercio and Tkac (2002) estimate for pension funds and in line with Petäjistö's (2013) estimate for moderately active retail mutual funds.[20] The average dollar has a strategy beta of 0.94. Thus, funds achieve performance with lower strategy-level risk, rather than by choosing lower risk benchmarks to make their performance look better.

Table A6 of the appendix presents results for alternative samples to evaluate the robustness of our results. The first column limits the sample to funds that enter the platform within a year after they are started. This restriction is potentially important because it restricts the analysis to funds with minimal amount of backfilling. Although we remove all backfilled data throughout this study, it is still possible that established and successful funds systematically differ from new funds. For this restricted sample, however, the alpha only marginally attenuates to an estimate of 81 basis points (t-value = 3.07).

The second column restricts the sample to post-2006. We use this cutoff for three reasons. First, the consultant's coverage, as a fraction of Pensions & Investments total assets under management, is higher after this date. Second, this part of the sample captures all of the crisis period. Third, GIPS® became the global standard for reporting performance in 2005.

[19] We list the 171 strategies and their benchmarks in Table A7 of the appendix.

[20] Petäjistö (2013) reports an average tracking error of 7.1% for actively managed retail mutual funds. He also estimates tracking errors by fund type, finding a tracking error of 15.8% for concentrated mutual funds, 10.4% for factor bets, 8.4% for stock pickers, 5.9% for moderately active funds, and 3.5% for closet indexers.

The gross alpha is 72 basis points (t-value = 2.05) for this sub-period. The third column restricts the sample to asset managers who report performance for funds representing at least 85% of their total institutional assets under management. We implement this restriction to evaluate whether fund performance varies with managers' reporting choices. We find similar results—113 basis points and a t-value of 3.23—even though the average number of funds drops from 4,648 for the full sample to 435 for this restricted sample.

Our finding that asset managers outperform both the asset-class and strategy-specific benchmarks before fees rejects the hypothesis that markets are fully efficient. If markets were fully efficient (Fama, 1970), all investment strategies would yield zero gross alphas. The fact that asset managers earn a gross alpha of 134 basis points per year across the four assets classes—or collectively extract $480 billion per year from the rest of the market—implies a degree of informational inefficiency. This wealth transfer, instead, is consistent with the notion that information acquisition is costly and, therefore, precludes the possibility of perfect informational inefficiency (Grossman and Stiglitz, 1980).

3.3 Mutual fund-benchmarked performance

Given the large academic literature on mutual fund performance, we next compare the performance of asset manager funds with the performance of mutual funds. We use mutual fund data from CRSP's survivorship-bias free database. For each asset manager strategy, we use the CRSP classification codes to identify all mutual funds that follow the same strategy. We follow Berk and Binsbergen (2015) and include all domestic actively managed mutual funds; that is, we do not exclude funds that invest in international assets. We compute value-weighted returns for these mutual funds grouped by strategy. Panel C of Table 4 reports the differences between the value-weighted returns earned by asset manager funds and mutual funds on both a gross and net basis.

The average asset manager fund's net return, from the perspective of a medium-sized institution, exceeds that of the average mutual fund by 110 basis points per year over the sample period. This difference is significant with a t-value of 2.43. This performance difference emanates from differences in gross performance and fees. In the comparison of gross returns, the average dollar invested in asset manager funds outperforms the dollar invested in mutual funds by 49 basis points; the difference in fees makes up for the remaining 61 basis points. The last row reports the average size of the mutual fund comparison group. Across all asset classes, we benchmark the average dollar invested in asset manager funds against 377 mutual funds. The asset-class breakdown shows that the performance differences, on both gross and net basis, are particularly large in the fixed income asset classes. The net return difference is positive but insignificant in U.S. public equity, and negative and insignificant in global public equity.

These estimates are consistent with the research on actively managed mutual funds. Fama and French (2010) show that, collectively, actively managed U.S. equity funds resemble the market portfolio. A comparison of asset manager funds against the gross return earned by mutual funds is therefore close to our broad asset class comparison, except that the mutual fund "benchmark" is a noisier version of the broad asset class. This additional noise may be the reason why the difference in gross returns is noisier than the differences in Panels A and B.

4 Amount of value added

Are some other asset managers more skilled than others, and how does the distribution of skill compare to that of mutual fund managers? We measure the amount of value that asset managers add as the product of the estimated gross alpha and the fund's assets under management (Berk and Binsbergen, 2015). The intuition is that gross alpha measures the total return extracted from the rest of the market. By construction, the value-weighted gross alpha across all investors equals zero. Multiplying the gross alpha by the assets under management therefore leads to a measure of the amount of money that an asset manager earns or loses at the expense of all other investors. Across all investors, these dollar measures of wealth transfers also add up to zero.

4.1 Compared with mutual funds

In Table 5, we report the distribution of value added for institutional asset managers and compare these estimates with estimates for retail mutual funds. In the first column, we report the distribution for all funds in our sample; in the second column, we remove strategies with less than one year of data. We compute, as before, gross alpha as the realized return in excess of the asset class-level benchmark. The estimates in these two columns are similar, suggesting that the results are not unduly influenced by any short-lived funds. The third column reports numbers for retail mutual funds, which we take from Table 3 of Berk and Binsbergen (2015). We use their "Vanguard Benchmark" specification, which benchmarks mutual funds against the returns of index funds.

The distribution for institutional asset managers is more spread out than the distribution for retail mutual funds. That is, at the tails of the distribution, institutional funds add or subtract far more value than what Berk and Binsbergen (2015) find in their mutual fund sample. These estimates are consistent with the typical asset manager fund being bigger than a mutual fund. In our sample, the median fund size across all asset classes is $419 million. The size of the median mutual fund—using the matched sample of funds from Panel C of Table 4—is just $31 million as of December 2012.

Asset manager funds display more skill than mutual funds. Berk and Binsbergen (2015) find that 57% of mutual funds have negative gross alphas, while only 45% of the funds in Table 5 have negative gross alphas.[21]

[21] Berk and Binsbergen (2015) benchmark returns against Vanguard index funds. Their index funds are net of fees and, because they are actual achievable returns, net of transaction costs. Our computation, which benchmarks asset managers against indices—rather than index funds—sets a higher standard than Berk and Binsbergen (2015). If we were to use index-fund benchmarks, these benchmarks would strictly underperform

4.2 Persistence in skill and client size

Berk and Binsbergen (2015) note that their t-values, such as those reported in Table 5, might be inflated if funds follow correlated strategies and the returns thus contain common shocks. Berk and Binsbergen (2015) measure persistence in the value-add measures to assess the statistical significance of the value-added measures. In Table 6, we use the same approach to confirm that the successful asset managers, as measured by the value add, are more likely to remain successful. In Panel A, we estimate monthly cross-sectional regressions in which the dependent variable is the fund's monthly value added and the explanatory variable is the fund's average value added over the previous 12 months. In the first column, the average coefficient is 0.85 with a t-value of 3.71 implying that value added is highly persistent. In the second column, we include strategy-level fixed effects to ensure that differences in strategies do not drive the persistence estimates. The estimate of persistence becomes more precise—the average coefficient is 0.83 with a t-value of 4.44.

We use this framework to measure the correlation between client sizes and managerial skill. In Panel B, we split the data series for each fund at the middle and regress its percentile rank in the value-added distribution for the second half on its percentile rank in the first half. We again find strong evidence of persistence in skill. The estimated coefficient on the percentile rank from the first half is 0.11 with a t-value of 8.74.

Asset managers differ in the types of clients they serve. One measure of client sophistication is the client's size. A large client, for example, would have the resources to manage assets in house and greater ability to search for skilled managers (Gârleanu and Pedersen, 2018). If a large client outsources despite having the resources to manage assets in house, the expected gain from doing so must be higher than that expected by a smaller, resource-constrained client. In the second column, we therefore add the percentile ranks of the fund's average client size and the manager's size to evaluate whether client and manager charac-

the benchmarks that we use in Table 5 because of fees and trading costs, thereby making asset managers look even better.

teristics from the first half of the sample predict the value added in the second half. In this specification, average client size positively predicts value added while manager size does not. Funds serving larger clients add more value; moving from the fund with the smallest clients to the largest clients moves the fund up 3.1 percentiles in the value-added distribution.

The result that client size predicts value added is consistent with the prediction of Gârleanu and Pedersen (2018) that a manager's client base is informative about its ability because more skilled managers have more large and sophisticated clients who engage in search. The fact that manager size does not predict value added is also consistent with Gârleanu and Pedersen (2018). The point of their model is that real-time, easily available signals should not be informative about differences in manager skill, and the authors use manager size as an example of one such signal (p. 1680).

The estimates in Table 6, together with the fee schedules reported in Figure 2, show that funds that serve larger clients are "better" in two dimensions: they extract more value from the rest of the market and they charge lower fees for their services. These estimates are consistent with larger clients having lower search costs, which is consistent with Gârleanu and Pedersen (2018), and more negotiation power when it comes to dividing the rents between the asset managers and clients, which is consistent with Pástor and Stambaugh (2012).

4.3 Is value added correlated across a manager's funds?

Is a manager that adds value in one fund more likely to add value in its other funds? We examine this question by regressing the amount of value that a manager added in one fund against the value the manager added in its other funds. If, for example, a manager has ten funds, we have ten observations. In the first observation, the dependent variable is the amount of value added in the first fund and the independent variable is the average value added in funds two through ten.

We present the results from these regressions in Table 7. Because the observations in this regression are, by definition, correlated within a manager via an adding-up constraint, we cluster standard errors by manager. We also include asset-class fixed effects. In the first column's regression, the slope coefficient is 0.54 with a t-value of 4.97. This estimate suggests that a manager who added value in one fund was likely to add value in the other funds.

A potential concern with the interpretation of these results is that an asset manager may follow correlated strategies. That is, even if a manager has ten funds, all of these funds may be of the same style (and take similar positions in the same assets), inducing correlations in the value adds. Because we have data on multiple asset classes, we can control for this mechanism by examining whether value added in one asset class correlates with value added in other asset classes.

In the second column, the dependent variable is again the fund's value added, but the independent variable is now the average value added in the manager's all other funds in the other asset classes. Because we restrict the analysis to managers who offer funds in multiple asset classes, the number of managers decreases by almost half. In this sample, the slope coefficient is 0.33 with a t-value = 5.64. That is, some managers are skilled in multiple asset classes while others are skilled in none. These estimates suggest that at least part of the variation in skill resides at the firm level and not solely at the level of the individual most responsible for each fund.

5 Informational inefficiency and fees

If markets were fully efficient, all investment strategies would yield zero alphas before fees, and there would be no reason for any active management: a client who pays any fees for active management would earn negative net alphas. All rational models of asset management therefore assume a degree of market inefficiency. This inefficiency is the *reason* for the existence of the industry.

In noisy rational expectations models of delegation, agents receive heterogeneous private signals about the value of a risky asset.[22] In these models, fees are informative about the quality of the fund manager's private signal. In Gârleanu and Pedersen (2018), for example, fees negatively correlate with market efficiency, defined as the variance of payoffs conditional on informed agents' signal to the variance of payoffs conditional on the price alone (Grossman and Stiglitz, 1980).

In this section, we test whether fees vary with informational inefficiency. We measure informational inefficiency as the volatility of the strategy's returns relative to the volatility of the broad asset class returns. The efficiency of the Small Cap Growth strategy, for example, is the standard deviation of returns of the average dollar invested in this strategy, scaled by the volatility of the average dollar invested in U.S. public equity. We assume that volatility within an asset class measures market inefficiency; the more prices fluctuate around fundamental values—that is, the expected payoff conditional on the signal—the greater the rents that informed agents can extract. In the context of Gârleanu and Pedersen (2018), this assumption would be equivalent to saying that, across strategies within an asset class, price volatility does not correlate perfectly with the payoff volatility.

In Figure 3, we plot relative fees against relative informational inefficiency for the 171 strategies across four broad asset classes. We rank all strategies based on their fees within the asset class and then assign the cheapest strategy a rank of zero and the most expensive strategy a rank of one. We similarly rank all strategies based on their informational inefficiency within each asset class. The solid red line is the linear regression line, which shows that relative fees increase in relative information inefficiency. The black dots represent the 171 strategies. The red circles represent bins of observations. We divide the x-axis into 25 segments of equal length; each group therefore contains approximately eight strategies. We plot the average fees for these bins.

In Table 8, we report the estimates of the regression of relative fees against our measure

[22] See, for example, Admati and Pfleiderer (1990), Ross (2005), Garcìa and Vanden (2009), and Gârleanu and Pedersen (2018).

of informational inefficiency. The point estimate of 0.50 for the slope has a standard error of 0.07. These estimates indicate that if we move from a strategy that lies at the 25th percentile of informational inefficiency to a strategy at the 75th percentile, the fee increases from the 37th to 63rd percentile. This estimate is consistent with asset managers charging higher fees for strategies operating in those market segments with greater informational inefficiency.

These estimates, together with the finding that institutional asset managers add value, therefore support the key foundation of rational models of the asset management industry: markets do not appear to be perfectly efficient, some asset managers profit from market inefficiencies, and the fees that they charge for their services increase in the inefficiency of the segment of the market in which they operate.

6 Sharpe (1992) analysis

How do asset managers generate positive gross alphas relative to strategy benchmarks? To address this question, we implement the Sharpe (1992) model that compares fund returns against portfolios of tradable indices that best mimic them.[23] We use this framework, first, to test whether asset managers achieve positive gross alphas with judicious choices of factor exposures and, second, to compute at what indifference cost institutions could have replicated asset manager returns by managing assets in house.

[23] An alternative approach would be to use the Fama-French three- or four-factor model to evaluate fund performance. We instead use the Sharpe (1992) model for several reasons. First, our goal is to compare fund performance with a benchmark in which institutions could have invested at reasonable transaction costs. We do so by using indices whose performance could have been captured by investing in either index or mutual funds. In contrast, as discussed by Berk and Binsbergen (2015), institutions could not have directly invested in the theoretical factor portfolios at reasonable transaction costs. These factors would be prohibitively expensive to trade because of their long-short nature and because they blend large and small stocks at a 50/50 ratio. Second, we examine the performance of both equity and fixed income strategies, and the Fama-French model does not contain fixed income-specific factors. Third, many of the equity strategies in the database are specific to countries besides the U.S. Griffin (2002) and Fama and French (2012) show that the Fama-French factors are country specific: a model with *local* factors is required to explain adequately the cross sections of size and value in each region. Hence, the global versions of the factors do not constitute a good benchmark for evaluating the performance of, for example, funds that invest in U.K. equity.

6.1 Estimating mimicking portfolios for asset manager funds from tradable factors

To implement the Sharpe analysis, we first define a set of tradable factors (that is, those with tradable indices). The returns on these indices represent theoretical returns; they do not reflect any fees or transaction costs. We modify the set of 12 original factors used in Sharpe (1992) to reflect changes in availability and market weights since the original paper. For example, we replace the Japanese market index with an emerging markets index. The following table lists the original factors used by Sharpe (1992) and those used in our analysis. The indices in bold represent our benchmarks for the broad asset classes.

Asset class	Sharpe (1992)	Our implementation
U.S. public equity	Sharpe/BARRA Value Stock	**Russell 3000**
	Sharpe/BARRA Growth Stock	S&P 500/Citigroup Value
	Sharpe/BARRA Medium Capitalization Stock	S&P 500/Citigroup Growth
	Sharpe/BARRA Small Capitalization Stock	S&P 400 Midcap
		S&P 600 Small Cap
Global public equity	FTA Euro-Pacific ex Japan	**MSCI World ex U.S.**
	FTA Japan	S&P Europe BMI
		MSCI Emerging Markets Free Float
U.S. fixed income	Salomon Brothers' 90-day Treasury Bill	**Barclays Capital U.S. Aggregate**
	Lehman Brothers' Intermediate Government Bond	U.S. 3-month T-Bill
	Lehman Brothers' Long-term Government Bond	Barclays U.S. Intermediate Government
	Lehman Brothers' Corporate Bond	Barclays Capital U.S. Long Government
	Lehman Brothers' Mortgage-Backed Securities	Barclays Capital U.S. Corporate Investment Grade
		Barclays Capital U.S. Mortgage-Backed Securities
Global fixed income	Salomon Brothers' Non-U.S. Government Bond	**Barclays Capital Multiverse ex U.S.**
		Barclays Capital Euro Aggregate Government
		Barclays Capital Euro Aggregate Corporate
		JP Morgan EMBI Global Diversified Index

For each fund, we regress monthly returns against a subset of the 18 factors using data up to month $t-1$. The subset of factors depends on the fund's asset class. For a U.S. equity fund, for example, the factors are Russell 3000 (the broad asset-class benchmark) and the six factors specific to U.S. public equity. We constrain the regression slopes to be non-negative and to sum to one (Sharpe, 1992): these regression slopes can therefore be interpreted as portfolio weights.[24] We then use the estimated loadings to construct a dynamic mimicking portfolio for each fund. An additional benefit of the Sharpe methodology, relative to an unconstrained regression of fund returns on the factors, is that the regression slopes are indicators of the styles that funds follow.[25]

Panel A of Table 9 reports the value-weighted averages of the factor weight estimates by broad asset class. For example, the average weight on the Russell 3000 (the broad asset class benchmark) for U.S. public equity funds is 9%. The remaining rows represent the deviations from the benchmark. For example, the average U.S. public equity fund holds a 32.3% weight in the S&P 500/Citigroup Value benchmark.

The second step of the Sharpe analysis assesses whether the factor loadings of the mimicking portfolio are the source of the positive abnormal fund performance. We estimate the factor loadings using rolling historical data to ensure that our second step performance measurement is out-of-sample.[26] For each fund-month, we calculate the fund's return in excess of the mimicking portfolio. Panel B of Table 9 reports monthly value-weighted average excess returns over the mimicking portfolio for each broad asset class and the associated t-statistics.

We find that the gross returns that asset managers generate are statistically indistinguishable from those of the mimicking portfolios for each asset class. The estimate for all asset classes is -0.07 with a t-value of -0.24. The estimated performance differences are both economically and statistically small; factor loadings therefore almost entirely account for the positive abnormal fund performance documented in Table 4. Because the mimicking

[24]We also estimated the regressions with the constraint that the sum of the coefficients is less than or equal to one. For this specification, the average weights sum to 0.99.

[25]Unconstrained regressions set high coefficients on some factors and negative coefficients on others when the left-hand-side strategy lies outside the span of those factors. Moreover, in an unconstrained regression, the regression coefficients do not need to sum up to 100%, and cannot therefore be interpreted as portfolio weights. Sharpe (1992, Table 2) gives an example that highlights the lack of interpretability of unconstrained regressions and, also, of regressions that constrain the weights to add up to 100% but that do not impose the $w \geq 0$ constraint on the weights.

[26]In Table A5 of the appendix, we present similar results when we estimate the Sharpe model using a jackknife procedure in which we use the full sample except for month t, or in which we exclude observations from six months before through six months after month t.

portfolios invest in theoretical indices, the gross alphas we report here are strictly lower than what they would if the benchmarks were tradable indices that accounted for trading costs. Table 9 suggests that funds effectively exchange lower strategy-level risk for factor risks. They outperform because the factors toward which they deviate outperform the strategy benchmarks.

Does performance generated through factor exposures represent skill? This question relates to Berk and Binsbergen (2015), who consider the proper benchmarking of mutual funds. If internal management by the client cannot reproduce the same factor exposure, then these authors suggest that we should attribute that exposure to a value-added activity that the fund provides its clients. Cochrane (2011) offers a similar interpretation:

> "I tried telling a hedge fund manager, "You don't have alpha. Your returns can be replicated with a value-growth, momentum, currency and term carry, and short-vol strategy." He said, "Exotic beta is my alpha. I understand those systematic factors and know how to trade them. My clients don't." He has a point. How many investors have even thought through their exposures to carry-trade or short-volatility... To an investor who has not heard of it and holds the market index, a new factor is alpha."

6.2 Do managers improve performance by timing factors?

We next examine managers' factors timing by abilities by measuring the extent to which asset managers improve performance by successfully tilting toward factors that are expected to earn high returns. To do so, we compute mimicking portfolios weights in two ways. First, we use the entire history of fund returns to find the mimicking portfolio. We call this the static mimicking portfolio because, if the fund shifts factor exposures, this approach returns the "average" exposures.[27] Second, we use a three-year rolling window around each month to

[27] Suppose, for example, that there are just two factors: value and size. A fund's loadings might be $\beta(value) = 1$ and $\beta(size) = 0$ in the first half of the sample and $\beta(value) = 0$ and $\beta(size) = 1$ in the second half. If so, the static weights would be $\beta(value) = 0.5$ and $\beta(size) = 0.5$.

find the mimicking portfolio. This short-window specification can identify changes in fund's factor exposures. We call this the dynamic mimicking portfolio.

We compute the returns on the static and dynamic portfolios and use them as benchmarks. If managers successfully time factors, then they should outperform the static mimicking portfolio more than they outperform the dynamic mimicking portfolio. Or, we can ignore the actual fund returns altogether and test directly whether the dynamic mimicking portfolio outperforms the static mimicking portfolio.

Panel C of Table 9 shows that, across all asset classes, the gap between the returns on the dynamic and static portfolios has a t-value of 1.95. This outperformance is mostly due to Global public equities, which have a t-value of 2.35. By contrast, the estimates for fixed income are statistically insignificant: -0.14 (U.S.) and 0.03 (Global). These estimates appear sensible. There are factors in fixed income as well—such as carry and momentum (Asness et al., 2013; Koijen et al., 2018)—but our sets of benchmarks may not adequately capture them, and so we could not observe managers timing these factors. It would therefore make sense for us to be able to identify outperformance, if there is any, only within equities. Equity factors might also have more predictable time variation in their premiums or investors might have more skill timing these factors.

The downside of this analysis is that both the dynamic and static portfolios are estimated with a considerable amount of noise. Because of the limited amount of data, the full-sample and the short-window portfolios are often close to each other. The returns on the two strategies are therefore also typically close to each other; the static strategy might earn 1.0% in one month while the dynamic might earn 1.05%. However, when we compute the test statistics for the differences in portfolio returns, we obtain reasonably precise estimates because some of this noise differences out. In the full sample, for example, the annualized return gap between the dynamic and static portfolios is only 0.12%, but the standard error of this gap is just 0.06%.

6.3 In-house implementation of factor index loadings

The results from the Sharpe analysis raise the question of whether institutional investors could have done as well as asset manager funds if they had instead implemented the factor portfolios in house. We examine this question by discarding our asset manager *return* data and constructing rolling optimal portfolios using only historical data on tradable factor indices. We treat the factor indices as the assets to generate mean-variance (MV) efficient portfolios separately for each of the four asset classes. We implement this optimization using data up to month $t-1$, and then calculate the return on the optimal portfolio for month t. We aggregate across asset classes by applying asset managers' month $t-1$ asset class weights for month t returns. To illustrate, suppose that a manager invests, as of month $t-1$, 50% in U.S. equity, 25% in U.S. fixed income, and 25% in global fixed income. We construct the optimal portfolios using information up to month $t-1$ separately for each of these three asset classes and then compute month t returns for them. Our proxy for in-house implementation, in this example, is the 50%-25%-25% weighted average of these three returns.

We modify the mean-variance algorithm in two ways to generate more stable optimal portfolios that avoid extreme short or long positions.[28] First, we set the covariance matrix to be diagonal to eliminate extreme loadings based on covariances. Second, following Campbell and Thompson (2007), we set any negative estimated risk premiums to zero.

Panel A of Table 10 presents the gross and net performance along with the implied Sharpe ratio for funds. Over the 2000–2012 period, funds earned 5.2% in gross returns with a standard deviation of 10.4% (Sharpe ratio = 0.3). Panel A then shows that the gross return on the replicating portfolio has a Sharpe ratio of 0.37.

In the rightmost column of Panel A, we report the cost that would make the average institution indifferent, in terms of the Sharpe ratio, between implementing the MV portfolio

[28] For a discussion of the measurement error issues associated with the standard mean-variance solution, see, for example, DeMiguel et al. (2009).

and delegating to asset managers. That is, the indifference cost solves for cost in:

$$\frac{r_{\text{gross replicating}} - r_f - \text{cost}}{\sigma_{\text{gross replicating}}} = \frac{r_{\text{net asset manager}} - r_f}{\sigma_{\text{net asset manager}}}. \tag{1}$$

We find that institutions would be indifferent between delegating and managing assets in house if the cost of managing assets in house was 85.5 basis points. This 85.5 basis points must cover both administrative costs and trading fees. In terms of administrative costs, Dyck and Pomorski (2012) find that large pension funds incur approximately 12 basis points in non-trading costs to administer their portfolios.

To assess the magnitude of the trading costs, we gather historical institutional mutual fund and ETF fee data from CRSP and Bloomberg covering the factors used in the replication. We present the time-series averages of these fees in Panel C. Using these series, we simulate the cost of implementing the replication for four different trading fee estimates: Quartile 1, Median, and Quartile 3 of the institutional mutual funds, sorted by cost, and the end-of-the-period ETFs. Panel B reports these results. Investing in the MV portfolio at the trading cost of the median institutional mutual fund would have cost 88.5 basis points in fees. Investing at the Quartile 1 fees would have cost 66.1 basis points. The indifference cost for the MV portfolio (85.5 basis points from Panel A) is similar to the sum of the administrative costs and the Quartile 1 fees (12 + 66.1 = 78.1 basis points). At this cost, an investor would be indifferent between managing assets in house and delegating assets. At any higher mutual fund fees, the investor would likely prefer delegating.

Importantly, Panel B shows that even the Quartile 1 trading-cost estimate is high relative to the end-of-period ETF fees. Although many ETFs were not available over the full sample period (Panel C reports the ETF inception dates), we consider a strategy that trades ETFs at their end-of-period fees. The first row of Panel B reports that, using the end-of-period ETF fees, the portfolio would have cost only 24 basis points, thus tilting the preference away from delegating to asset managers toward investing in house. The introduction of liquid, low cost ETFs is likely eroding the comparative advantage of asset managers.

This analysis is subject to several caveats. First, we assume that the necessary liquidity is available for the ETFs, index funds, and institutional mutual funds that an institution would use to replace delegation. Second, we assume that all institutions face the same trading costs. Third, we assume that institutions are sophisticated. Institutions must know which factors could be used to improve performance, and they have to know how to implement the required loadings in real time. Fourth, institutions may be willing to earn a lower Sharpe ratio from delegating that what they could earn in house to shield themselves from blame.[29] These caveats favor delegation: less-sophisticated institutions or institutions that receive other non-pecuniary benefits from asset managers would likely choose delegation over in-house management.

7 Conclusions

Institutional investors, rather than investing passively, often delegate to active strategies provided by asset managers. From 2000 to 2012, institutional investors delegated an average of $36 trillion (29% of worldwide investable assets) per year to asset managers, paying 44 basis points per dollar invested. If markets are efficient and the arithmetic of active management of Sharpe (1991) holds even approximately (Pedersen, 2018), this behavior represents a puzzle. Why do institutions delegate if, by doing so, they earn negative net alphas?

We show that the assumptions behind this puzzle—markets are efficient and active investors must lose—do not appear to be satisfied: institutions' delegated assets outperformed strategy benchmarks by 88 basis points gross, or 44 basis points net of fees for medium-sized institutions. We trace this outperformance to systematic deviations from the asset-class benchmarks. The rise in the ETF market is, however, likely eroding the advantages that

[29] Jones and Martinez (2017) and Cookson et al. (2019) note that this shielding-from-blame mechanism may also, in part, contribute to the widespread use of consultants for due diligence.

asset managers held during our sample period.

Our results relate to the literature on who pays for financial intermediation through fees and returns. If we apply the estimates of Philippon (2015) and Greenwood and Scharfstein (2013) to total worldwide investable capital in 2012, the worldwide cost of securities intermediation was $726 billion. We can compare this top-down estimate with bottom-up calculations for costs incurred by different classes of investors. The U.S.-based estimates of French (2008) and Bogle (2008), applied globally, imply that the intermediation costs for retail delegation through mutual funds was approximately $100 billion for 2012. Barber et al.'s (2009) estimates of retail investor trading costs from Taiwan can be scaled up to the global level and adjusted for differences in turnover, leading to an estimate of $313 billion in costs for non-delegated individual trading in 2012.[30] We find that institutions paid $210 billion in fees in 2012 for delegated intermediation, suggesting that the costs incurred by institutions for managing assets in house were approximately $100 billion.

With respect to returns, we find that the average intermediated institutional dollar's return exceeded that of the market by 134 basis points between 2000 and 2012. This estimate implies that the average non-institutional or non-intermediated dollar—that is, investments made through retail mutual funds, directly by individuals or institutions, or by asset managers who do not engage consultants—underperformed the market by 55 basis points even before fees.

Our results suggest that the average institutional asset manager is skilled (Admati and Pfleiderer, 1990; Ross, 2005; Garcìa and Vanden, 2009), that asset managers share the rents they extract with their clients (Pástor and Stambaugh, 2012), and that institutions engage in costly search to find skilled managers (Gârleanu and Pedersen, 2018). In Gârleanu and Pedersen (2018), investors share some of the rents because investors who search for skilled

[30] Barber et al. (2009) estimate that commissions cost individual investors 0.7% of GDP in Taiwan. If we adjust for the high turnover in Taiwan, their estimate suggests that individual traders incur $313 billion in fees annually worldwide. We thank Brad Barber and Robin Greenwood for data and guidance with these calculations.

managers must recover their search costs. In addition, asset managers appear to compete with each other: they typically offer the same fund at a markedly lower fee when the client's allocation is very large. Because a single fund is often offered at very different fees, investors' expected net alphas cannot all be zero.

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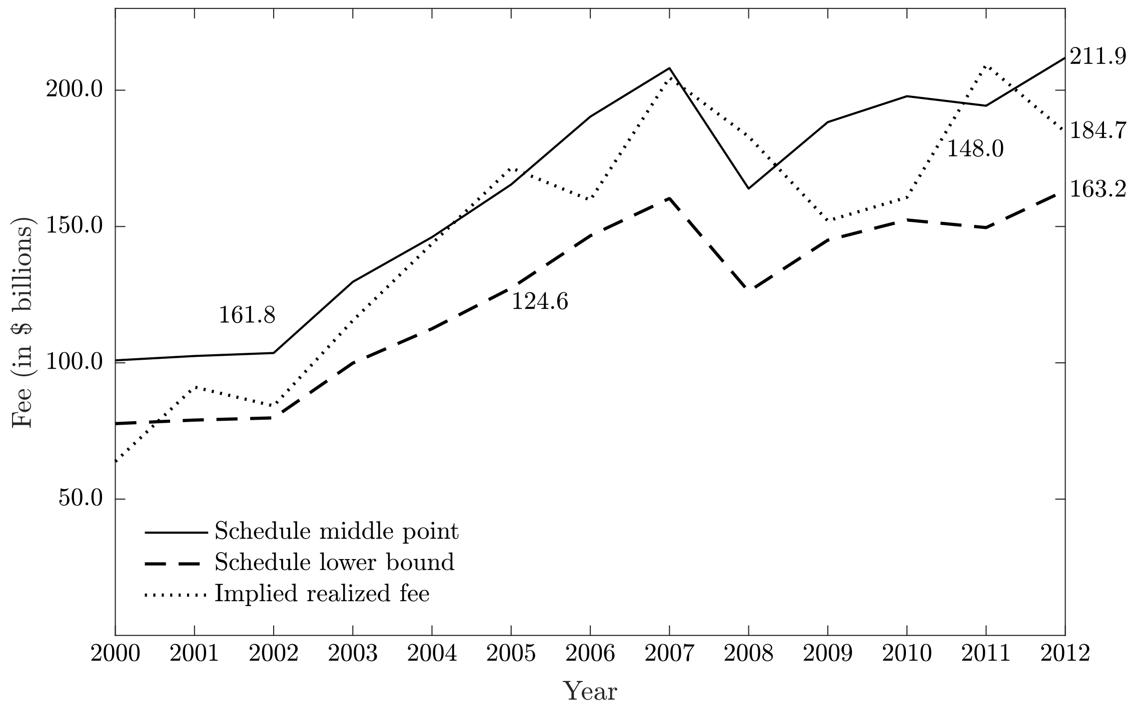

Figure 1: **Aggregate fees paid by institutions to asset managers.** This figure presents aggregate fee estimates based on information available in the Consultant's database. The estimates represent value-weighted average fees in the Consultant's database multiplied by total institutional assets under management from annual surveys by Pensions & Investments. Line "Schedule middle point" assumes that the average dollar in each fund pays the median fee listed on that fund's fee schedule and "Schedule lower bound" uses the lowest fee from each fee schedule. "Implied realized fee" is estimated using data on funds that report returns both gross and net of fees. We annualize the monthly return difference, take the value-weighted average, and then re-weight asset classes so that each asset class's weight matches that in the full database. The numbers on y-axis to the right are the aggregate fee estimates for 2012. The numbers within the figure represent the average annual fees over the sample period for the three sets of estimates.

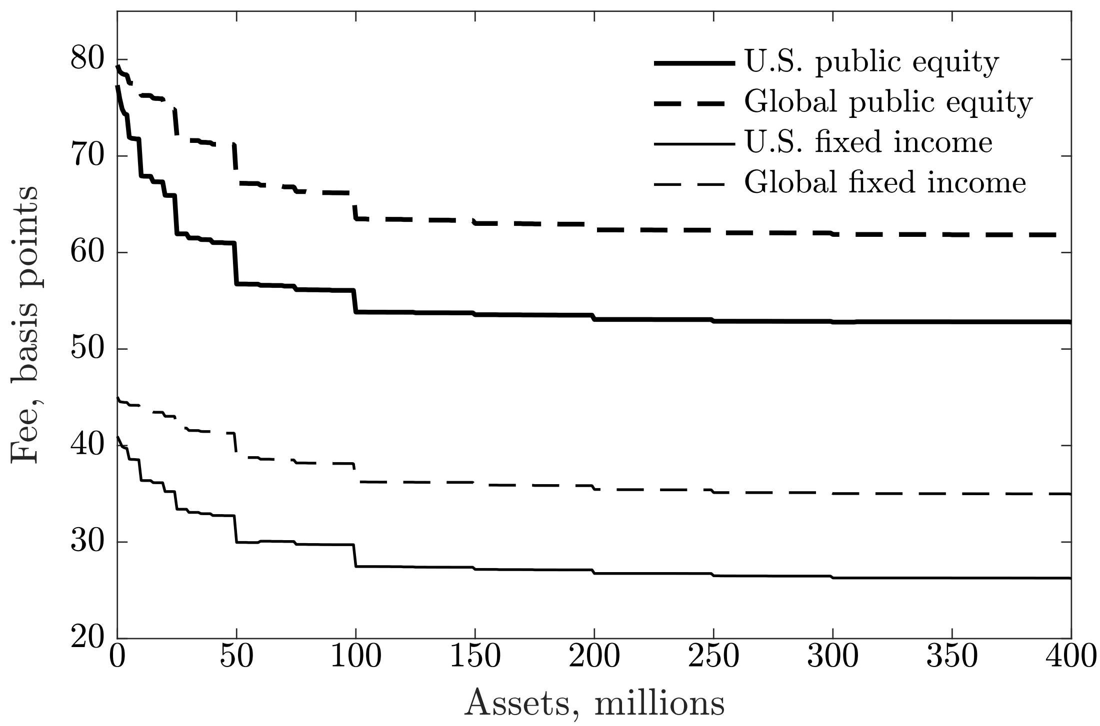

Figure 2: **Average fee schedules by asset class.** This figure presents average fee schedules for the U.S. public equity, global public equity, U.S. fixed income, and global fixed income broad asset classes in the Consultant's database. The amount on the y-axis is the fee applied to an investment in excess of the amount indicated on the x-axis. We compute the fee applied to investments ranging from the first dollar up to $400 million. When an asset manager offers a fund through multiple vehicles (e.g., a segregated account and an institutional mutual fund), we compute an equal-weighted average over the vehicles to get a fund-level fee schedule.

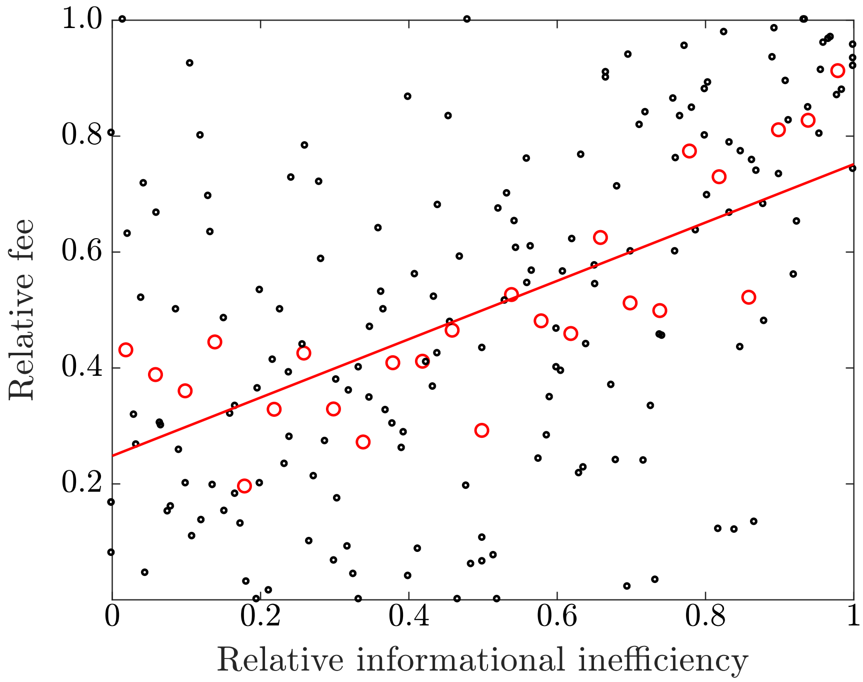

Figure 3: **Informational inefficiency and fees.** We measure informational inefficiency as the ratio of the volatility of strategy returns to the volatility of broad asset class returns. We measure returns on average dollars invested in each strategy or entire broad asset class across all asset managers. In this figure, we plot relative fees against relative information inefficiency for 171 strategies across the four broad asset classes. We rank all strategies based on their fees within the broad asset class and assign the cheapest strategy a rank of zero and the most expensive strategy a rank of one. We similarly rank all strategies based on their informational inefficiency within each broad asset class. The black dots in this graph represent the 171 strategies. The red circles in this graph represents bins of observations. We divide the x-axis into 25 segments of equal length; each bin therefore contains approximately eight strategies. We plot the average fees for these bins. The solid red line is the linear regression line. This regression line, unlike the individual points, is based on the raw strategy-level data. The point estimates and standard errors of this line are reported in Table 8.

Table 1: Assets under management ($ in billions)

This table presents our estimates of worldwide investable assets, and descriptive statistics for the Pensions & Investments surveys and the Consultant's database. For our estimates of worldwide investable assets and descriptions of the Pensions & Investments surveys, see the appendix. The Consultant's data cover the period 2000–2012.

	Worldwide investable assets	Pensions & Investments		Consultant's database			
				AUM		AUM with returns	
Year	Total	Total	% of WIA	Total	% of P&I	Raw	Without backfill
2000	78,884	22,170	28.1%	6,760	30.5%	5,709	3,276
2001	75,512	22,628	30.0%	7,049	31.1%	5,900	3,956
2002	76,603	22,897	29.9%	7,367	32.2%	6,409	4,479
2003	93,933	28,616	30.5%	10,097	35.3%	8,615	6,556
2004	108,514	32,370	29.8%	11,838	36.6%	10,543	8,409
2005	116,104	36,619	31.5%	13,309	36.3%	12,235	9,745
2006	134,293	42,142	31.4%	16,382	38.9%	15,308	12,642
2007	157,057	46,208	29.4%	29,176	63.1%	26,237	22,962
2008	134,650	36,306	27.0%	23,123	63.7%	19,485	17,099
2009	152,190	41,712	27.4%	26,693	64.0%	22,702	20,811
2010	164,610	43,798	26.6%	28,000	63.9%	24,767	23,184
2011	163,093	42,978	26.4%	27,501	64.0%	24,612	23,579
2012†	172,566	46,832	27.1%	27,944	59.7%	24,959	24,598
Average	125,231	35,790	28.9%	18,095	47.6%	15,960	13,946

† Year 2012 Consultant assets as of June 2012.

Table 2: Summary of fund characteristics by asset class

This table presents descriptive statistics for the funds in the Consultant's database. Panel A reports the number of managers and funds, the average fund age, and the average assets under management for all funds. "All" includes public equities and fixed income; the other four asset classes (asset blends, cash, hedge funds, and other alternatives) are not included in the main sample. In Panel B, we calculate each month the distributions of assets, client counts, and assets under management per client for each fund and then report the time series averages of these distributions. Total assets and assets per client are in millions of U.S. dollars. Panel C reports average returns, standard deviations, and Sharpe ratios for asset managers funds, the broad asset class benchmarks, and the strategy-specific benchmarks. The estimates are reported by asset class. The return on the strategy-specific benchmark is the value-weighted average of all the strategies within each asset class, with the weights proportional to funds' assets under management. Row "All" reports the performance of equity and fixed income asset classes. The Consultant's data cover the period from January 2000 through June 2012.

Panel A: Number of managers and funds and average assets under management

Asset class	Number of managers	Number of funds	Average fund age	Total AUM per year ($M)	% of total AUM
All	2,194	16,130	12.1	9,686,516	100%
U.S. public equity	1,236	5,022	12.7	2,739,913	28%
Global public equity	1,088	6,360	11.0	2,815,470	29%
U.S. fixed income	594	2,239	14.7	2,335,466	24%
Global fixed income	440	2,509	10.9	1,795,668	19%
	Asset classes not included in the main sample				
Asset blends	638	1,819	15.7	701,401	Not included
Cash	287	641	14.7	850,894	Not included
Hedge funds	1,553	4,340	7.9	843,079	Not included
Other alternatives	366	953	9.5	193,250	Not included

Panel B: Distributions of assets, client counts, and assets under management per client

		Percentiles		
Asset class	Mean	25	50	75
All				
Assets	1,884.6	110.9	419.3	1,415.5
Clients	248.7	1.8	6.5	22.1
AUM per client	294.7	12.7	55.3	171.6
Assets by asset class				
U.S. public equity	1,496.2	85.7	350.0	1,152.9
Global public equity	1,725.0	109.2	415.1	1,452.9
U.S. fixed income	2,675.8	169.1	540.8	2,039.4
Global fixed income	2,227.0	152.6	501.2	1,568.5
		Asset classes not included in the main sample		
Asset blends	2,136.3	88.6	371.9	1,343.2
Cash	3,857.7	127.0	469.1	1,831.8
Hedge funds	1,287.4	58.7	185.6	636.0
Other alternatives	1,030.9	116.1	394.4	1,061.3

Panel C: Average returns, standard deviations, and Sharpe ratios for funds, broad asset class benchmarks, and strategy-specific benchmarks

	Asset managers			Asset-class benchmark			Strategy benchmark		
Asset class	Avg. return	SD	Sharpe ratio	Avg. return	SD	Sharpe ratio	Avg. return	SD	Sharpe ratio
All	5.23	10.33	0.30	3.75	9.78	0.16	4.82	10.37	0.26
U.S. public equity	4.46	16.69	0.14	3.31	16.65	0.07	4.23	16.55	0.12
Global public equity	4.00	16.87	0.11	1.98	15.53	−0.01	3.66	17.30	0.09
U.S. fixed income	7.10	3.90	1.26	6.36	3.61	1.16	6.83	4.22	1.10
Global fixed income	7.03	4.85	1.00	6.35	8.50	0.49	6.02	4.61	0.83
	Other asset classes not included in the main sample								
Asset blends	3.76	6.72	0.24	4.18	11.04	0.18			
Cash	3.20	0.76	1.36	3.88	1.61	1.06			
Hedge funds	2.72	3.53	0.16	2.54	3.50	0.11			
Other	10.71	12.82	0.67						

Table 3: Fees by asset class and client size

This table reports the distributions of fund fees across all asset classes and by asset class. The fees reported in this table are the middle point fees reported on each fund's fee schedule. The fees are computed using data on a total of 13,027 funds. The number of funds in the average month is 4,797.

	Average			Percentiles		
Asset class	VW	EW	SD	25	50	75
All	44.0	55.8	33.6	31.0	53.4	74.3
U.S. public equity	49.2	63.1	37.7	47.2	63.5	80.0
Global public equity	58.2	68.1	45.8	50.6	64.0	80.6
U.S. fixed income	28.7	29.5	20.6	21.1	26.8	35.1
Global fixed income	31.9	36.1	24.6	22.9	29.5	44.1

Table 4: Evaluating fund returns against broad market indices, strategy-specific benchmarks, and mutual funds

This table presents gross and net alphas from single-factor models that use the four broad asset class benchmarks listed in Table A4 (Panel A); the 171 strategies listed in Table A7 (Panel B); and mutual funds that follow the same strategy as each asset manager fund (Panel C). In Panels A and B, we first estimate fund-by-fund regressions of net and gross returns against benchmarks and collect $e_{it} = \hat{\alpha}_i + \hat{\varepsilon}_{it}$. We then estimate value-weighted panel regressions of these residuals against a constant, clustering the standard errors by month. The weights in this regression are proportional to each fund's assets under management and they are scaled to sum up to one within each month. Betas and R^2s reported are obtained by estimating similar value-weighted regressions with the fund-specific betas and R^2s as the dependent variables. Tracking error estimates are obtained from value-weighted regressions of e_{it}^2s on a constant. Alphas and tracking errors are annualized. We compute three net returns that apply to institutions of different sizes: small institutions pay the highest fee on the fund's fee schedule, medium institutions pay the median fee, and large institutions pay the lowest fee. Column "Constraint: $\beta = 1$" in Panel A sets funds' betas against broad asset class benchmarks equal to one. In Panel C, we compare the performance of asset manager funds with the performance of mutual funds. For each asset manager fund, we use the CRSP classification codes to identify all mutual funds that follow the same strategy. We then compute the value-weighted return series of these mutual funds using the CRSP survivorship-bias free database. Panel C reports the differences between the value weighted gross and net returns earned by asset manager funds and mutual funds. The number of mutual funds at the bottom is the average number of funds against which a dollar invested in each asset manager fund is compared. The Consultant's data cover the period from January 2000 through June 2012.

Panel A: Value-weighted performance against broad market indices

	All		Asset Class			
	Unconst.	$\beta = 1$	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
Gross $\hat{\alpha}$	1.91	1.34	0.96	1.75	0.92	4.36
	(3.95)	(3.26)	(1.90)	(1.35)	(1.80)	(4.94)
Net $\hat{\alpha}$						
Small institution	1.35	0.78	0.33	1.02	0.56	3.95
	(2.78)	(1.88)	(0.66)	(0.78)	(1.08)	(4.48)
Medium institution	1.48	0.90	0.47	1.18	0.64	4.04
	(3.04)	(2.19)	(0.93)	(0.91)	(1.24)	(4.58)
Large institution	1.58	1.00	0.58	1.30	0.72	4.11
	(3.25)	(2.43)	(1.15)	(1.00)	(1.39)	(4.66)
$\hat{\beta}$	0.93	1.00	1.00	1.05	0.97	0.47
Tracking error	7.9%	7.9%	8.0%	9.4%	4.1%	6.6%
R^2	70.0%		85.6%	77.1%	64.3%	35.3%
Avg. no. of funds	4,647.9	4,647.9	1,783.5	1,540.9	776.7	546.7

Panel B: Value-weighted performance against strategy-specific benchmarks

	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
		Asset Class			
Gross $\hat{\alpha}$	0.88	0.41	0.62	1.35	1.33
	(3.45)	(1.03)	(1.34)	(6.51)	(3.26)
Net $\hat{\alpha}$					
Small institution	0.32	−0.21	−0.11	0.98	0.93
	(1.24)	(−0.53)	(−0.24)	(4.74)	(2.26)
Medium institution	0.44	−0.08	0.05	1.06	1.02
	(1.73)	(−0.19)	(0.10)	(5.13)	(2.49)
Large institution	0.55	0.04	0.17	1.14	1.09
	(2.13)	(0.09)	(0.37)	(5.51)	(2.66)
$\hat{\beta}$	0.94	0.98	0.96	0.84	0.95
Tracking error	5.6%	6.3%	6.0%	2.9%	4.9%
R^2	82.3%	89.8%	90.3%	73.5%	69.3%
Avg. no. of funds	4,647.9	1,783.5	1,540.9	776.7	546.7

Panel C: Value-weighted performance against mutual funds

	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
		Asset Class			
Difference in gross returns	0.49	0.08	−2.07	0.71	3.34
	(1.07)	(0.14)	(−1.96)	(1.01)	(2.68)
Difference in net returns					
Small institution	0.97	0.59	−1.37	1.28	3.46
	(2.15)	(1.00)	(−1.30)	(1.82)	(2.77)
Medium institution	1.10	0.74	−1.22	1.37	3.56
	(2.43)	(1.26)	(−1.16)	(1.95)	(2.85)
Large institution	1.20	0.87	−1.11	1.46	3.62
	(2.66)	(1.49)	(−1.05)	(2.08)	(2.90)
Average number of:					
Asset manager funds	2,690.8	2,073.3	2,309.9	929.3	930.1
Mutual funds	376.6	844.7	100.6	187.8	333.4

Table 5: Value added: Institutional asset managers versus mutual funds

This table presents estimates of how much value asset managers add and then compares these estimates for mutual funds. To estimate value added, we follow Berk and Binsbergen (2015) and multiply the fund's estimated gross alpha for month t by its assets under management for month $t-1$. The first column presents estimates for our full sample of asset manger funds. In the second column, we drop asset manager funds with less than one year of data. The rightmost column shows the "Vanguard Benchmark" specification estimates from Table 3 of Berk and Binsbergen (2015). The cross-sectional weighted means, standard errors of the weighted means, and t-statistics are computed by weighting by the number of periods the fund exists.

	Institutional asset managers		Mutual funds (from Berk and Binsbergen)
	All	$T \geq 12$	
Cross-sectional weighted mean	1.13	1.14	0.27
Standard error of the weighted mean	0.16	0.16	0.05
t-Statistic	6.89	6.95	5.74
Cross-sectional mean	0.90	1.02	0.14
Standard error of the mean	0.22	0.20	0.03
t-statistic	4.06	5.20	4.57
1st percentile	−26.24	−22.69	−3.60
5th percentile	−5.88	−5.61	−1.15
10th percentile	−2.41	−2.30	−0.59
50th percentile	0.02	0.02	−0.02
90th percentile	3.46	3.44	0.75
95th percentile	8.19	7.98	1.80
99th percentile	39.66	37.31	7.82
Percent with less than zero	45.4%	45.2%	57.0%
No. of Funds	11,029	10,767	5,974

Table 6: Value added: Persistence

This table presents estimates of the persistence of value added. To estimate value added, we follow Berk and Binsbergen (2015) and multiply the fund's estimated gross alpha for month t by its assets under management for month $t-1$. Panel A presents the average coefficients and the associated t-statistics for cross-sectional regressions of the fund's monthly value added on the fund's average value added for the previous 12 months. In Panel B, we split the each fund's monthly value added at the mid-point of its data series and then regress the percentile rank of the fund's second half value added on its first half percentile rank of value added. We calculate the percentile ranks within each strategy. In addition, we include as predictors the percentile ranks of the fund's average client size and the manager's total assets under management during the first half of its data series. t-statistics are reported in parentheses.

Panel A: Month ahead performance

	Value added month $t+1$	
Average value added over months t to $t-11$	0.85	0.83
	(3.71)	(4.44)
Strategy-level fixed effects	No	Yes
Months	137	137

Panel B: Performance during second vs. first half

	Value added during second half	
Value added during first half	0.11	0.10
	(8.74)	(5.73)
Average client size during first half		0.03
		(2.33)
Manager size during first half		−0.01
		(−0.71)
Strategy-level fixed effects	Yes	Yes
Adj. R^2	15.7%	18.0%
N	4,986	4,986

Table 7: Value added: Across funds

In this table, we examine whether the fund's value added is associated with the value added by the other fund's managed by the asset management firm. To estimate value added, we follow Berk and Binsbergen (2015) and multiply the fund's estimated gross alpha for month t by its assets under management for month $t-1$. The dependent variable is the fund's average monthly value added. In the first column, the independent variable is the average monthly value added by all other funds managed by the asset management firm. In the second column, the independent variable is the average monthly value added by all other funds not in the fund's asset class managed by the asset management firm. t-statistics clustered at the manager level are reported in parentheses.

	Fund's value added	
	All asset classes	Excluding fund's asset class
Value added for manager's other funds	0.54	0.33
	(4.97)	(5.64)
Asset-class fixed effects	Yes	Yes
Adj. R^2	1.8%	1.1%
N	10,500	8,646

Table 8: Informational inefficiency and fees

This table reports estimates from a regression that measures the association between fees and informational inefficiency. We regress relative fees against relative information inefficiency for the 171 strategies across the four broad asset classes. We rank all strategies based on their fees within the broad asset class and assign the cheapest strategy a rank of zero and the most expensive strategy a rank of one. We measure informational inefficiency as the ratio of the volatility of strategy returns to the volatility of broad asset class returns. We measure returns on average dollars invested in each strategy or entire broad asset class across all asset managers. We then rank all strategies based on their informational inefficiency within each broad asset class. t-statistics are reported in parentheses.

	Relative fee
Constant	0.25
	(6.25)
Relative informational inefficiency	0.50
	(7.14)
N	171
Adjusted R^2	24.9%

Table 9: Sharpe analysis

This table reports estimates from an analysis that compares fund returns with returns on mimicking portfolios constructed from 18 factors. We implement this analysis using a modified version of Sharpe's (1992) approach. For each fund i-month t, we regress the strategy returns against the factors using data up to month $t-1$. The first factor is the strategy's broad asset class benchmark listed in Table A4. The remaining factors, which are listed in Panel A, are specific to each broad asset class. The regression slopes are constrained to be non-negative and to sum up to one. We use the resulting slope estimates to compute the return on strategy i's mimicking portfolio in month t and define a residual $e_{it} = r_{it} - r_{it}^{B}$, where r_{it}^{B} is the return on the mimicking portfolio. We then estimate a value-weighted panel regression of these residuals against a constant, clustering the errors by month. The weights in this regression are proportional to each fund's assets under management and they are scaled to sum up to one within each month. Panel A reports the average weights by asset class. Panel B reports gross alphas, tracking errors, and information ratios for the funds by asset class. The tracking error and Sharpe weight estimates are obtained from value-weighted regressions of e_{it}^2s and the first-stage weights on a constant. Panel C examines the extent to which managers successfully tilt toward factors that are expected to earn high returns. To do so, we first use the entire history of fund returns to generate a static mimicking portfolio. Second, we use a three-year rolling window around each month to generate a mimicking portfolio. We report the returns on the dynamic and static mimicking portfolios. The Consultant's data cover the period from January 2000 through June 2012.

Panel A: Sharpe weights ($w_1 + \cdots + w_{15} = 100\%$)

		Asset Class			
Factors	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
Asset-class benchmark	21.1				
Russell 3000		9.0			
MSCI World ex U.S.			30.5		
Barclays Capital U.S. Aggregate				23.9	
Barclays Capital Multiverse ex U.S.					28.6
Equity					
S&P 500/Citigroup Value	12.1	32.3	5.2		
S&P 500/Citigroup Growth	11.2	27.3	10.6		
S&P 400 Midcap	4.1	11.5	2.4		
S&P Small Cap	5.7	14.6	3.2		
S&P Europe BMI	9.6	2.2	31.7		
MSCI Emerging Market Free Float Adjusted Index	5.7	3.2	16.3		
Fixed income					
U.S. 3 Month T-Bill	5.9			11.4	20.9
Barclays Capital US Intermediate Govt	3.5			10.7	5.6
Barclays Capital US Long Govt	3.6			7.4	10.2
Barclays Capital US Corporate Investment Grade	7.2			21.0	9.1
Barclays Capital US Mortgage Backed Securities	4.3			14.9	2.5
Barclays Capital Euro Aggregate Govt	0.6			0.1	3.9
Barclays Capital Euro Aggregate Corporate	0.5			0.3	2.0
JP Morgan EMBI Global Diversified	4.9			10.2	17.2
Total	100.0	100.0	100.0	100.0	100.0
Avg. number of funds	4,216.0	1,629.7	1,383.1	712.8	490.5

Panel B: Excess returns over the mimicking portfolio

		Asset Class			
	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
Gross $\hat{\alpha}$	−0.07	−0.60	−0.63	0.47	1.12
	(−0.24)	(−1.70)	(−0.77)	(1.15)	(1.71)
Tracking error	6.0%	5.9%	7.6%	3.2%	5.1%
R^2	83.6%	89.2%	84.7%	66.4%	58.6%
Avg. no. of funds	4,216.0	1,629.7	1,383.1	712.8	490.5

Panel C: Returns on dynamic and static mimicking portfolios

	Mimicking portfolio			
Asset class	Dynamic	Static	Difference	t-value
All	5.49	5.37	0.12	1.95
U.S. public equity	5.12	5.02	0.10	0.92
Global public equity	5.01	4.75	0.26	2.35
U.S. fixed income	6.52	6.54	−0.01	−0.14
Global fixed income	6.39	6.39	0.00	0.03

Table 10: Replicating asset managers

This table compares the performance of asset managers to a replicating portfolio constructed from the tradable indices listed in Panel A of Table 9. The replicating portfolio is computed by diagonalizing the covariance matrix, constraining the estimated risk premiums to be nonnegative, and maximizing the Sharpe ratios as in Markowitz (1952) We estimate the means and covariances using all available historical data for each index up to month $t-1$. We construct the replicating portfolio separately within each asset class, and then use these weights together with the asset-class weights observed in the asset-manager data to compute the return on the replicating portfolio in month t. Panel A reports the Sharpe ratios of asset managers and the replicating portfolio. Column "Indifference cost (bps)" equates the Sharpe ratio of the replicating portfolio with the asset managers' Sharpe ratio. Panel B reports the cost of holding the replicating portfolio using four alternative assumptions about fees. The detailed fees are reported in Panel C. Expense ratios and fees are reported in basis points. Entries of "NA" denote that the data are not available.

Panel A: Sharpe ratios and indifference costs of replicating portfolios

	Average return	SD	Sharpe ratio	Indifference cost (bps)
Asset managers				
Gross return	5.23%	10.38%	0.295	
Net return	4.79%	10.38%	0.252	
Replicating portfolio, gross return	6.43%	11.55%	0.369	85.5

Panel B: Cost (bps) of investing the replicating portfolio using the actual fees of the vehicle over the period

Vehicle	Fee
Institutional mutual funds	
Quartile 1	66.1
Median	88.5
Quartile 3	112.4
End-of-sample ETFs	24.0

Panel C: Fees used in the replicating portfolios

Benchmark	ETFs: Expense ratio	ETFs: Ticker	ETFs: Start date	Institutional mutual funds: Q1	Institutional mutual funds: Median	Institutional mutual funds: Q3	Fee used in replication
S&P 500/Citigroup Value	15	SPYV	9/29/00	70	91	112	91
S&P 500/Citigroup Growth	15	SPYG	9/29/00	80	97	122	97
S&P 400 Midcap	15	IVOO	9/9/10	70	95	115.5	95
S&P Small Cap	15	SLY	11/15/05	85	109	135	109
S&P Europe BMI	12	VGK	3/10/05	54.5	88	129	88
MSCI Emerging Market Free Float Adjusted	67	EEM	4/11/03	102	139	166	139
U.S. 3 Month T-Bill	14	BIL	5/30/07	16	26	45	26
Barclays Capital US Intermediate Govt	20	GVI	1/5/07	51	66	83	66
Barclays Capital US Long Govt	12	VGLT	11/24/09	20	43	67	43
Barclays Capital US Corporate Investment Grade	15	LQD	7/26/02	55	70	92	70
Barclays Capital US Mortgage Backed Securities	32	MBG	1/15/09	49	65	80	65
Barclays Capital Euro Aggregate Govt	15	GOVY	5/23/11	NA	NA	NA	15
Barclays Capital Euro Aggregate Corporate	20	IBCX	3/17/03	NA	NA	NA	20
JP Morgan EMBI Global Diversified	40	EMB	12/19/07	84	97	112	97

Appendix

In this appendix, we describe the methodology that we use to estimate worldwide investable assets and total institutional assets held by asset managers.

Worldwide investable assets

We estimate total worldwide investable assets, which represent the sum of six broad investable asset classes: real estate, outstanding government bonds, outstanding bonds issued by banks and financial corporations, outstanding bonds issued by non-financial corporations, private equity, and public equity.

For real estate, we estimate the worldwide value of commercial real estate. To do so, we follow the methodology used by Prudential Real Estate Investors (PREI) in the report "A Bird's Eye View of Global Real Estate Markets: 2010 Update." Their methodology uses GDP per capita to capture country-level economic development and estimates the size of a country's commercial real estate market based on GDP. They select a time-varying threshold and assume that the value of commercial real estate above this threshold is 45% of total GDP. The threshold starts in 2000 at $20,000 in per capita GDP and then adjusts annually by the U.S. inflation rate. For countries with per capita GDP below the threshold in a given year, PREI calculates the value of the country's commercial real estate market as:

$$\text{Value of commercial real estate} = 45\% \times \text{GDP} \times (\text{GDP per capita / Threshold})^{1/3}.$$

To estimate the worldwide size of the government, financial, and corporate bond sectors, we use the Bank for International Settlements' debt securities statistics provided in Table 18 of the Bank's Quarterly Reviews. These statistics present total debt securities by both residence of issuer and classification of user (non-financial corporations, general government, and financial corporations).[31] We then aggregate the country-level data by year. For private equity, we use Preqin's "2014 Private Equity Performance Monitor Report," which provides annual estimates of assets under management held by private equity funds worldwide and these estimates include both cash held by funds ("dry powder") and unrealized portfolio values. For our estimates of the size of world's public equity markets, we use the World Bank's estimates of the market capitalization of listed companies.[32]

Table A2 presents annual estimates of worldwide investable assets by the six broad asset classes. Our estimate of worldwide investable assets for 2012 is $173 trillion. For comparison, if we extrapolate Philippon's (2015) estimates of U.S. investable assets, we obtain a similar estimate of $175 trillion in worldwide investable assets for 2012.

[31] The data are available at `https://www.bis.org/statistics/hanx18.csv`.

[32] The data are available at `http://data.worldbank.org/indicator/CM.MKT.LCAP.CD`.

Total institutional assets held by asset managers

In our analysis, we supplement the Consultant's database with data from Pensions & Investments Magazine, which implements annual surveys of the asset management industry. In this subsection, we describe the Pensions & Investments surveys and how we use the surveys to construct our estimates of total institutional assets under management held worldwide by asset managers, which are presented in the first column of Table 1.

We use two Pensions & Investments surveys. The first survey is the Pensions & Investments Towers Watson World 500, which is an annual survey of the assets under management (retail and institutional) held by the world's 500 largest money managers. The second survey is the Pensions & Investments Money Manager Directory, which provides more detailed data for U.S.-based money managers including total assets under management, institutional assets under management, and broad asset allocations (equity, fixed income, cash, and other) for U.S. tax exempt institutional assets.

Table A3 provides descriptive statistics for these surveys and describes how we construct our estimate of total worldwide institutional assets held by asset managers. Column (1) presents annual total worldwide assets under management (retail and institutional assets) based on the Pensions & Investments Towers Watson World 500 survey and column (2) presents total assets under management (retail and institutional assets) for the U.S.-based asset managers covered in the Pensions & Investments Money Manager Directory survey. The totals presented in these two columns include both retail and institutional assets. In column (3), we therefore present total institutional assets held by U.S.-based asset managers. As shown in column (4), over the sample period, institutional assets held by U.S.-based asset managers range from 63% to 69% of total assets.

To estimate the worldwide size of the institutional segment, we extrapolate based on the institutional asset percentages for the U.S.-based asset managers. We first create a union of managers who show up on either the Pensions & Investments Towers Watson 500 survey or the Pensions & Investments Money Manager Directory survey.[33] Column (5) presents total assets under management (retail and institutional) for the managers in the union of the two surveys. These totals are very close to the totals based on the Towers Watson 500 survey, implying that the top 500 managers control the vast majority of assets. We next scale the total assets presented in column (5) by the percent institutional assets held by U.S.-based managers presented in column (4). Column (6) presents these estimates of worldwide institutional assets under management, which we present in the first column of Table 1.

[33] Missing in this union are non-U.S.-based asset managers who are smaller than the cutoff for the Pensions & Investments Towers Watson World 500. Given the close estimates of the top 500 with the intersection with U.S.-based managers, this missing category does not appear large.

Table A1: Institutional assets under advisement by the top investment consultants ($ in billions)

This table presents estimates of the total institutional assets under advisement by the top investment consultants. These estimates are based on annual surveys carried out by Pensions & Investments.

Year	Total institutional assets	Total U.S. institutional assets	Consultants surveyed
2004	13,075	9,729	96
2006	14,746	12,025	88
2008	15,369	10,353	98
2009	16,428	9,932	105
2010	21,521	12,851	104
2011	24,807	14,495	106
2012	31,172	15,483	114

Table A2: Estimates of worldwide investable assets ($ in billions)

This table presents annual estimates of worldwide investable assets by asset class and in aggregate. We use the following sources to estimate the worldwide investable assets by asset class: real estate, Prudential Real Estate Investors; government bonds, the Bank for International Settlements; corporate bonds, the Bank for International Settlements; private equity, Preqin; public equity, the World Bank.

Year	Real estate	Govt. bonds	Financial bonds	Corporate bonds	Private equity	Public equity	Total
2000	13,249	13,578	14,613	4,788	716	31,940	78,884
2001	13,085	13,210	15,927	4,924	751	27,614	75,512
2002	13,625	15,361	18,386	5,216	767	23,248	76,603
2003	15,373	18,686	21,808	5,540	870	31,657	93,933
2004	17,312	21,750	25,091	5,727	963	37,671	108,514
2005	18,641	21,205	26,913	5,413	1,238	42,694	116,104
2006	20,100	22,600	31,426	5,801	1,704	52,663	134,293
2007	22,667	24,852	37,077	6,437	2,276	63,748	157,057
2008	24,770	28,055	38,298	6,757	2,279	34,491	134,650
2009	23,104	32,187	40,199	7,535	2,480	46,685	152,190
2010	25,251	36,686	38,434	8,102	2,776	53,361	164,610
2011	28,005	39,745	37,866	8,565	3,036	45,876	163,093
2012	28,481	41,181	37,799	9,380	3,273	52,452	172,566

Table A3: Total institutional assets held by asset managers ($ in millions)

This table presents how we estimate total institutional assets held by asset managers. To do so, we use two Pensions & Investments surveys: Towers Watson and the Money Manager Directory. Towers Watson provides the total assets under management (retail and institutional) held by the world's 500 largest asset managers, which are presented in the first column. The Money Manager Directory provides total assets under management (retail and institutional) and institutional assets under management for U.S. asset managers, which are presented in the second and third columns. We create a union of these two surveys and then use the ratio institutional to total assets for U.S. asset managers to extrapolate total worldwide institutional assets held by asset managers, which is presented in the last column.

	Towers Watson	Money Manager Directory			Union	
	Total AUM	Total AUM	Institutional AUM	Institutional %	Total AUM	Institutional AUM
2000	34,590,284	20,192,354	12,805,136	63%	34,959,252	22,169,678
2001	34,683,588	20,896,204	13,481,972	65%	35,072,352	22,628,247
2002	35,002,040	20,371,588	13,192,112	65%	35,357,876	22,896,843
2003	42,461,288	24,965,260	16,622,492	67%	42,978,752	28,616,324
2004	48,183,548	28,726,436	19,072,168	66%	48,754,880	32,369,531
2005	52,964,400	31,701,564	21,643,876	68%	53,635,800	36,619,222
2006	62,902,888	37,344,564	24,708,774	66%	63,693,416	42,142,311
2007	68,731,120	41,645,204	27,621,568	66%	69,667,872	46,207,863
2008	52,581,856	31,414,800	21,459,676	68%	53,147,692	36,305,571
2009	61,149,820	37,957,556	25,607,218	67%	61,829,884	41,712,151
2010	63,811,204	43,089,043	29,233,620	68%	64,556,904	43,798,420
2011	62,170,700	42,591,797	29,157,459	68%	62,780,420	42,978,170
2012	67,223,072	46,757,542	32,237,746	69%	67,925,128	46,832,082

Table A4: Broad asset classes in the Consultant's database and their benchmarks

This table presents the annual average returns and standard deviation of returns for both the funds in the four broad asset classes and the benchmarks used in Table 4 to evaluate funds performance.

	Consultant's database		Benchmark		
Asset class	Average return	SD	Name	Return	SD
U.S. public equity	4.46	16.69	Russell 3000	3.29	16.66
Global public equity	4.01	16.87	MSCI World ex U.S.	2.03	15.55
U.S. fixed income	7.10	3.90	Barclays Capital U.S. Aggregate	6.29	3.60
Global fixed income	7.03	4.85	Barclays Capital Multiverse ex U.S.	6.36	8.61

Table A5: Sharpe analysis: Alternative specifications

This table reports estimates from an analysis that compares fund returns with returns on mimicking portfolios constructed from 18 factors. In Table 9, we construct the mimicking portfolio by using data only up to month $t-1$. In Panel A of this table, we construct the mimicking portfolio using data for all months except month t. In Panel B, we construct the mimicking portfolio using data that exclude the six months both before and after month t. We report gross alphas, tracking errors, and information ratios for the funds by asset class.

Panel A: Exclude month-t return observation (jackknife)

		Asset Class			
	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
Gross $\hat{\alpha}$	−0.11	−0.57	−0.78	0.42	1.00
	(−0.33)	(−1.55)	(−1.00)	(1.22)	(1.66)
Tracking error	6.5%	6.8%	7.7%	3.2%	5.0%
R^2	82.0%	86.6%	83.7%	67.2%	60.0%
Avg. no. of funds	4,583.5	1,762.1	1,517.7	765.4	538.3

Panel B: Exclude return observations in window $[t-6, t+6]$

		Asset Class			
	All	U.S. public equity	Global public equity	U.S. fixed income	Global fixed income
Gross $\hat{\alpha}$	−0.10	−0.59	−0.85	0.51	1.14
	(−0.32)	(−1.60)	(−1.08)	(1.42)	(1.90)
Tracking error	6.6%	7.1%	7.8%	3.2%	5.1%
R^2	81.2%	85.7%	83.4%	66.7%	59.8%
Avg. no. of funds	4,407.9	1,709.5	1,446.3	742.2	509.9

Table A6: Evaluating fund returns against strategy-specific benchmarks: Robustness

This table presents gross and net alphas from single-factor models that use the 171 strategies listed in Table A7 based on alternative samples for robustness. The first column limits the sample to funds for which the manager entered no more than one year of historical data at the initiation of coverage. The second column presents results for the post-2006 data and the third column limits the sample to asset managers that report performance for funds that represent at least 85% of their total assets under management. We first estimate fund-by-fund regressions of net and gross returns against benchmarks and collect $e_{it} = \hat{\alpha}_i + \hat{\varepsilon}_{it}$. We then estimate value-weighted panel regressions of these residuals against a constant, clustering the standard errors by month. The weights in this regression are proportional to each fund's assets under management and they are scaled to sum up to one within each month. Betas and R^2s reported are obtained by estimating similar value-weighted regressions with the fund-specific betas and R^2s as the dependent variables. Tracking error estimates are obtained from value-weighted regressions of e_{it}^2s on a constant. Alphas and tracking errors are annualized. The Consultant's data cover the period from January 2000 through June 2012.

	Sample or specification		
	No more than one year of historical data	Only post-2006 data	Strategy coverage $\geq$ 85%
Gross $\hat{\alpha}$	0.81	0.72	1.13
	(3.07)	(2.05)	(3.23)
Net $\hat{\alpha}$			
Small institution	0.23	0.17	0.49
	(0.88)	(0.48)	(1.41)
Medium institution	0.37	0.28	0.63
	(1.39)	(0.82)	(1.80)
Large institution	0.48	0.38	0.75
	(1.80)	(1.08)	(2.14)
$\hat{\beta}$	0.93	0.94	0.93
Tracking error	5.3%	5.4%	5.5%
R^2	83.2%	80.8%	81.6%
Avg. no. of funds	2,406.1	6,488.0	434.6

Table A7: Strategies in the Consultant's database and their benchmarks

Strategy name	Number of funds	Average return	Benchmark	Average return
U.S. public equities				
All Cap Core	145	3.5	Russell 3000	3.6
All Cap Growth	90	1.8	Russell 3000 Growth	1.3
All Cap Index Based	18	3.1	Russell 3000	3.6
All Cap Value	88	7.8	Russell 3000 Value	5.8
Canada Core	145	9.1	S&P/TSX 60	9.3
Canada Growth Biased	57	9.2	MSCI Canada Growth	9.2
Canada Income Oriented	38	9.2	S&P/TSX Income Trust	16.5
Canada International Equity Targeted Volatility	2	12.2	MSCI AC World Minimum Volatility CAD	9.9
Canada Passive Equity	32	10.2	S&P/TSX Composite	9.0
Canada Small Cap Equity	79	11.0	MSCI Canada Small Cap	8.7
Canada Socially Responsible	16	8.4	Jantzi Social	8.4
Canada Total Equity	85	7.3	S&P/TSX Composite	7.6
Canada Value Biased	74	10.2	MSCI Canada Value	8.9
Large Cap Core	738	2.7	S&P 500	3.0
Large Cap Growth	575	0.7	S&P 500/Citigroup Growth	1.9
Large Cap Index Based	199	3.7	S&P 500	3.0
Large Cap Value	573	5.7	S&P 500/Citigroup Value	4.2
Other	215	3.1	Russell 3000	3.6
Mid Cap Core	114	7.8	Russell Midcap	8.3
Mid Cap Growth	172	4.3	Russell Midcap Growth	4.8
Mid Cap Index Based	34	9.1	Russell Midcap	8.3
Mid Cap Value	142	8.8	Russell Midcap Value	10.3
Small Cap Core	220	7.8	S&P 600 Small Cap	9.9
Small Cap Growth	295	4.8	S&P SmallCap 600/Citigroup Growth	8.8
Small Cap Index Based	46	7.6	S&P U.S. SmallCap	4.8
Small Cap Micro	75	8.9	Russell Microcap	7.5
Small Cap Value	292	10.7	S&P SmallCap 600/Citigroup Value	10.8
SMID Cap Core	82	8.9	S&P 400 MidCap (50%) S&P 600 Small Cap (50%)	9.7
SMID Cap Growth	123	2.9	S&P MidCap 400/Citigroup Growth (50%) S&P SmallCap 600/Citigroup Growth (50%)	8.4
SMID Cap Value	102	10.5	Russell Midcap Value	10.3
Socially Responsible	88	3.0	Jantzi Social	5.7
Global public equity				
Asia ASEAN Equity	47	9.3	MSCI South East Asia	16.6
Asia ex Japan Equity	151	9.3	MSCI AC Asia (Free) ex Japan	8.5
Asia Greater China Equity	67	14.9	MSCI Golden Dragon	14.4
Asia Pacific Basin Equity Passive	19	13.8	MSCI AC Asia Pacific (Free)	7.1
Asia/Pacific Small Cap Equity	20	14.4	MSCI AC Asia Pacific ex Japan Smallcap	10.5
Asian Emerging Markets Equity	26	14.6	MSCI EM ASIA	13.1
Australia Equity	323	6.3	S&P Australia BMI	7.5
Australia Equity (Socially Responsible)	23	7.7	Jantzi Social	8.7
Australia Passive Equity	22	7.6	S&P Australia BMI	8.4
Australia Small Company Equity	71	11.0	S&P/ASX Emerging Companies	9.2
BRIC Equity	57	18.5	MSCI BRIC	19.0
China Equity (offshore)	38	18.3	MSCI China (USD)	22.0
Eastern European Equity	47	13.0	MSCI EM Eastern Europe	12.7
EMEA Equity	36	15.1	MSCI EM Eastern Europe	11.4
Emerging Markets Equity	305	10.4	MSCI EM Net	13.5
Emerging Markets Equity Other	59	11.2	MSCI EM Net	13.5
Equity Sectors Consumer Goods	13	7.2	MSCI World	0.2
Equity Sectors Other	17	8.4	MSCI AC WORLD	6.4
Europe Eurozone Equity	171	2.9	MSCI EMU	2.3
Europe ex U.K. Equity	157	5.5	MSCI Europe ex U.K.	4.4
Europe ex U.K. Equity - Passive	15	6.5	MSCI Europe ex U.K.	6.1
Europe inc U.K. Equity	382	3.2	S&P Europe BMI	5.1
Europe inc U.K. Equity - Passive	12	7.5	S&P Europe BMI	7.2
Europe Nordic Equity	33	−0.3	MSCI Nordic	−0.4
Europe Norway Equity	45	1.9	MSCI Norway	7.1
Europe Small Cap Equity	101	5.1	MSCI Europe Small Cap	7.3
Europe Sweden Equity	31	5.1	MSCI Sweden	5.7
Flexible Equity	54	0.7	MSCI World	3.1
German Equity	20	3.3	DAX	3.4

Strategy name	Number of funds	Average return	Benchmark	Average return
Global Equity - Core	631	2.2	MSCI World	3.1
Global Equity - Growth	152	0.8	MSCI World Growth	1.5
Global Equity - Passive	76	0.5	MSCI World	4.6
Global Equity - Value	204	5.5	MSCI World Value	4.6
Global Small Cap Equity	57	4.3	MSCI World Small Cap Index	7.2
Gold & Precious Metals	15	26.2	S&P GSCI Precious Metals Total Return	18.7
Health/Biotech	23	7.1	S&P Healthcare Equip Sel	11.1
HK ORSO	58	4.3	Hang Seng TR Index	14.9
Hong Kong Equity	34	16.2	FTSE MPF Hong Kong	13.9
Indian Equity	54	18.6	MSCI India	19.4
International Equity Global Equity Sustainability	7	13.4	MSCI EM	1.3
International Equity Global Equity Sustainability	167	4.2	MSCI World ESG	−0.8
International Equity Global Equity Sustainability	4	3.3	MSCI World ESG	13.2
International Equity Targeted Volatility	20	4.0	MSCI World Minimum Volatility	5.1
International Equity World ex Japan Equity	116	2.2	MSCI World	5.1
Japan Equity	417	−2.2	MSCI Japan	−0.8
Japan Passive Equity	28	1.6	MSCI Japan	4.0
Japan Small Cap Equity	55	3.9	MSCI Kokusai All Cap	0.5
Korea Equity	23	7.2	MSCI Korea	10.5
Latin American Equity	40	14.9	MSCI Latin America	17.0
Mixed U.K./Non-.UK. Equity	27	7.1	FTSE All Share	3.4
Natural Resources	45	13.4	S&P Global Natural Resources SK	−8.9
New Zealand Equity	46	8.5	NZX 50 (40 prior to 1 Oct 2003)	7.2
Other	75	3.7	MSCI World	3.1
Pacific Basin ex Japan Equity	149	9.6	MSCI Pacific ex Japan	10.7
Pacific Basin inc Japan Equity	85	3.4	MSCI Pacific	2.1
Singapore Equity	17	10.0	MSCI Singapore	10.7
Swiss Equity	67	7.1	MSCI Switzerland	6.9
Technology	24	0.6	MSCI AC World: Sector: Information Technology	−1.2
U.K. All Cap	309	4.2	MSCI U.K.	4.0
U.K. Passive Equity	44	5.3	MSCI U.K.	4.6
U.K. Small Cap	50	8.1	Hoare Govett Smaller Companies	8.0
U.K. Socially Responsible	15	4.2	MSCI World ESG	−0.8
World ex U.S./EAFE Equity - Core	341	2.8	MSCI EAFE	3.4
World ex U.S./EAFE Equity - Growth	142	1.9	MSCI EAFE Growth	1.6
World ex U.S./EAFE Equity - Passive	52	3.4	MSCI EAFE	3.4
World ex U.S./EAFE Equity - Value	146	6.8	MSCI EAFE Value	5.2
World ex U.S./EAFE Small Cap Equity	78	7.1	MSCI EAFE Small Cap	7.9
U.S. fixed income				
Bank/Leveraged Loans	58	5.9	S&P/LSTA U.S. Leveraged Loan 100 Index Price	0.3
Canada Short-Term	13	4.5	DEX Short Term	4.6
Canada Core Plus	34	6.3	DEX Long Term	8.1
Canada Credit	23	7.4	DEX Universe Corporate	6.7
Canada Long-Term	32	8.3	DEX Long Term	8.5
Canada Other	65	8.4	DEX Long Term	8.8
Canada Passive	33	7.4	DEX Universe Bond	6.3
Canada Universe	152	6.6	DEX Universe Bond	6.6
Convertible	47	3.7	Barclays Capital U.S. High Yield Composite	8.0
Core Investment Grade	399	6.3	Barclays Capital U.S. Corporate Inv Grade	7.0
Core Opportunistic	158	6.8	Barclays Capital U.S. Aggregate	6.4
Credit	65	6.7	Barclays Capital U.S. Universal	6.5
Credit - Long Duration	34	7.9	Barclays Capital U.S. Long Credit	7.3
Fixed Income Private Debt	12	12.1	Preqin Buyout	12.9
Government	66	7.1	Barclays Capital U.S. Govt/Credit	6.5
High Yield	174	7.1	Barclays Capital U.S. High Yield Composite	8.0
Index Based	98	6.5	Barclays Capital U.S. TIPS	8.0
Intermediate	242	6.0	Barclays Capital U.S. Intermediate Aggregate	6.0
Liability Driven Investment	29	7.9	Barclays Capital U.S. Corporate Inv Grade	7.5
Long Duration	81	9.9	Barclays Capital U.S. Long Credit	8.9
Mortgage Backed	96	8.3	Barclays Capital U.S. Mortgage Backed Securities	6.2
Municipal	113	5.1	SPDR Nuveen Barclays Capital Municipal Bond Fund ETF	2.1
Other	111	6.0	Barclays Capital U.S. Aggregate	6.4
Real Estate Other	9	27.8	FTSE EPRA/NAREIT Global ex U.S. EUR	2.6
Socially Responsible	9	6.4	Barclays Capital U.S. Universal	6.3
TIPS/Inflation Linked Bonds	65	7.9	Barclays Capital U.S. TIPS	7.4

Strategy name	Number of funds	Average return	Benchmark	Average return
Global fixed income				
Asia ex Japan Bonds	24	4.0	Barclays Capital Non-Japan Asia USD Credit	7.1
Asia Singapore Bond	22	3.6	Singapore iBoxx ABF Bond Index	4.0
Asian Bonds	55	6.8	JP Morgan Asia Credit Index JACI	7.6
Australia Credit	18	6.4	UBS Credit	6.4
Australia Diversified	26	7.1	UBS Composite Bond	6.3
Australia Enhanced Index	14	6.4	UBS Composite Bond	6.3
Australia Fixed Income	72	6.3	UBS Composite Bond	6.3
Australia Inflation Linked Bonds	21	6.8	UBS Inflation	7.1
Australia Passive	11	6.3	UBS Composite Bond	6.3
Australia Short Duration - High Income	48	6.2	BofAML Global High Yield	11.3
Denmark Fixed Income	13	6.3	OMRX Bond	5.5
Emerging Markets Debt	144	12.0	JP Morgan EMBI Global Diversified	10.9
Emerging Markets Debt - Corporate	24	22.2	BofA Merrill Lynch Emerging Markets Corporate	16.2
Emerging Markets Debt - Local Currency	70	11.1	JPMorgan Government Bond Index - Emerging Markets	11.6
Europe Sweden Fixed Income	10	7.0	OMRX Bond	5.2
Eurozone Bank Loans	11	−6.0	S&P European Leveraged Loan Index	3.7
Eurozone Govt	97	7.6	Barclays Capital Euro Aggregate Gov	5.0
Eurozone Govt & Non-Govt	133	4.5	Barclays Capital Euro Aggregate Credit	4.9
Eurozone High Yield	48	4.7	BofAML Euro High Yield Index	7.4
Eurozone Inflation-Linked Bonds	22	3.0	Barclays Capital Euro Inflation Linked Bond Indices	3.3
Eurozone Non-Govt	113	4.6	Barclays Capital Euro Aggregate Corporate	5.0
Eurozone Other	24	2.7	Barclays Capital Euro Aggregate Credit	4.3
Eurozone Passive	25	4.7	Barclays Capital Euro Aggregate Credit	4.3
Global Broad Market/Aggregate	165	6.0	Barclays Capital Global Aggregate	6.4
Global Convertibles	54	3.7	UBS Global Convertible Index	7.5
Global Credit	84	6.3	Barclays Capital Global Aggregate	5.7
Global High Yield	71	8.2	BofAML Global High Yield	9.1
Global Inflation-Linked Bonds	45	5.9	Barclays Global Inflation Linked Index	6.2
Global Passive	34	7.4	Barclays Capital Global Aggregate	6.8
Global Sovereign	187	7.1	JP Morgan GBI Global	6.7
Hong Kong Dollar Bond	18	3.5	HSBC Hong Kong Bond	4.5
International Fixed Other	12	7.8	Barclays Capital Global Aggregate	6.0
International Multi-asset Fixed Other	8	8.6	Barclays Capital Global Aggregate	5.3
Japan Fixed Income	101	0.5	Nikko BPI Composite	1.5
New Zealand Fixed Income	15	7.1	UBS Composite Bond	6.5
Other	37	3.6	Barclays Capital Global Aggregate	6.4
Swiss Fixed Income	44	3.5	Swiss Bond Index Total Return	2.5
U.K. Core Plus	69	6.9	BofAML Non Gilts AAA Rated	6.0
U.K. Europe Other	1	9.2	BofAML Non Gilts 10+ Year	12.1
U.K. Govt & Non-Govt	62	6.9	BofAML Non Gilts AAA Rated	6.1
U.K. Index Linked Gilts	48	7.0	FTSE Gilts ILG All Stocks	6.9
U.K. Non-Govt	81	6.7	BofAML Non Gilts All Stocks	6.2
U.K. Passive Fixed Income	39	7.5	BofAML Non Gilts	5.6
U.K. Govt	71	6.4	FTSE Gilts All Stocks	6.2
Unconstrained Bond	46	7.7	Barclays Capital Global Aggregate	5.5
World ex Japan	83	4.1	Barclays Capital Global Aggregate	6.5
World ex U.S.	51	7.7	Barclays Capital Global ex U.S.	6.6