The Risk of Outsourcing: How External Advisors Influence Mutual Fund Performance

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ABSTRACT

Mutual fund families increasingly outsource the portfolio management task to external advisors. The high-powered incentive contract offered to external advisors, presumably an optimal outcome, implicitly creates convexity in their payoff. We provide causal evidence that this convexity makes the conditional portfolio choice of outsourced mutual funds about twice as risky as in-house funds, which leads to their underperformance. However, fund families can curb excessive risk-shifting unconditionally by: invoking the reputation of external advisor(s) when marketing the fund (co-branding) and hiring geographically proximate external advisors (co-location). Hiring multiple external advisors simultaneously (co-management) is also effective, specifically when underperforming.

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1 Introduction

Outsourcing of investment advisory functions is growing across the delegated portfolio management industry. As of 2024, more than 30% of equity mutual funds, accounting for approximately 15% ($0.74 trillion) of total assets under management (AUM), delegated their investment management to an external unaffiliated advisor. The decision to outsource can be driven by the capacity constraints of mutual fund families, the ambition to gain market share by expanding their product offerings in new investment styles, or the ability to extract cost efficiencies by dividing work along the lines of specialization (Debaere and Evans (2015), and Massa and Schumacher (2020)). However, the growing popularity of outsourcing the investment advisory function does not necessarily imply an increase in investor welfare. Chen et al. (2013), in their seminal paper, find that outsourced funds underperform in-house managed funds by about 52 basis points a year. Chuprinin et al. (2015), Moreno et al. (2018) and Broman et al. (2023) also confirm this finding in different samples that use both domestic and international mutual funds.

In this paper, we investigate the source of outsourced funds' underperformance and argue that it arises from contracting frictions between two key parties: the fund family and the external investment advisor. Our central contribution is to show that the equilibrium contract incentivizes external advisors to engage in strategic mid-year risk-shifting—rather than curb risk-taking—an outcome that is inefficient from the investor's perspective. Importantly, this risk-shifting motive differs from previously documented drivers such as performance maximization (e.g., Lee et al. (2019)) or flow incentives (e.g., Brown et al. (1996)).

The agency problems we examine stem from the firm boundaries between the fund family and the external advisor. These boundaries prevent the fund family from coordinating with the external advisor and controlling some of the key drivers of fund success, such as manager assignment, compensation design, and monitoring mechanisms. Chen et al. (2013) argue that, in this imperfect informational environment, offering external advisors contracts with high-powered incentives can be optimal. They empirically demonstrate the prevalence of such contracts by showing that outsourced funds are more likely to be closed for poor performance—a pattern we confirm in our sample as well.

Yet such contracts can create unintended consequences by making the advisor's payoff option-like. Underperformance raises the likelihood of contract termination and thus drives the payoff toward zero, a risk that is especially stark given that the median advisor in our sample manages only *one* fund. Outperformance, by contrast, increases the likelihood of contract retention and preserves fee income tied to AUM. The steep trade-off between retention and termination makes employment risk especially salient for outsourced advisors. Although performance-based fee components such as fulcrum fees can be economically meaningful in certain sub-advisory arrangements, Elton et al. (2003) and Ma et al. (2019) report that they apply to fewer than 5% of advisors, suggesting that termination risk creates the more pervasive incentive in practice. In this environment, high-powered contracts may lead outsourced advisors to strategically increase portfolio risk in the second half of the year, conditional on mid-year performance. Specifically, advisors with returns close to the benchmark face the strongest incentive to "swing for the fences," since their implicit asymmetric payoff structure amplifies the value of taking volatility. In other words, we expect the outsourced advisors to maximize the vega of the option embedded in the contract.[1] Importantly, this incen-

[1]Maximizing asset growth is an important goal as most investment advisors, including outsourced advisors,

tive dissipates once performance strays meaningfully above or below the benchmark. We refer to this channel as the *retention hypothesis* of risk-shifting, and argue that the resulting increase in conditional risk-taking—rather than underinvestment in risk, as in Chen et al. (2013)—helps explain why outsourced funds underperform in-house funds.

Given that a large percentage of fund families outsource the fund management to advisory firms, we next consider what tools, if any, they use to complete contracts in the presence of firm boundaries and to mitigate risk-shifting. First, we look at *co-branded* funds. Often, fund families partner with unaffiliated external advisors and put the advisors' names in the fund name to attract flows using the advisors' reputations *(co-branded)*. The reputation cost, due to co-branding, can be effective in assuaging potential conflicts of interest and reducing risk-shifting (see Moreno et al. (2018)). Second, geographical proximity matters for effective monitoring (see Kang and Kim (2008) and Jensen et al. (2015)). Therefore, we expect to observe less risk-shifting when we focus on funds where the fund family and the advisor(s) are located nearby (*co-located*). Third, we look at *co-managed* funds. When there are multiple advisors managing the same fund (*co-managed*), firm boundaries among them limit the extent of collusion and promote effective peer-monitoring (see Kandel and Lazear (1992)). Demonstrating an association between these mechanisms and reduced conditional risk-shifting would further support our central hypothesis, highlighting the prevalence of contractual arrangements to mitigate performance attrition and justify the popularity of outsourcing fund management.

have AUM-based compensation (Section 205(a)(1) of the Investment Advisers Act of 1940). However, this compensation depends on retaining the advisory contract, which is evaluated based on fund performance. Additionally, due to the tournament nature of the flow-performance relation (Brown et al. (1996) and Sirri and Tufano (1998)), funds near the middle of the performance distribution—the region most relevant for our analysis—face weak AUM-gathering incentives.

To empirically test our hypotheses, we use the universe of U.S. equity mutual funds from 1999 to 2024. Our baseline results show that the distance of fund performance from the benchmark is inversely related to the risk-shifting ratio (the ratio of the second period's return standard deviation to the first period's return standard deviation). These findings reinforce the original conclusions of Lee et al. (2019), who report that asymmetric compensation contracts offered by the investment advisor to the portfolio manager of a fund incentivize the manager to strategically risk-shift. However, more importantly, consistent with the *retention hypothesis* of risk-shifting, we find that the observed inverse relationship is significantly higher for outsourced funds than for those managed in-house. In fact, outsourced funds (coef: -1.643) engage in about 100% more strategic risk-shifting than in-house (coef: -0.853) managed funds when the fund performance is close to the benchmark returns. Given that, on average, risk-shifting leads to poor fund performance (see Huang et al. (2011)), the nearly twofold increase in the coefficient is clearly economically very significant.

On account of firm boundaries and weaker monitoring by the outsourcing fund family, the portfolio managers hired by advisors of outsourced funds could exploit the asymmetry in the compensation contract more than managers of in-house funds. We refer to the combined effect of managerial compensation and weaker monitoring as the *nexus hypothesis* of risk-shifting. To further support the *retention hypothesis* of risk-shifting and rule out the role of portfolio manager compensation, we exploit the heterogeneity in the portfolio manager's compensation contracts (using hand-collected data) and show that outsourced funds with performance-based compensation do not change their portfolio risk materially differently from those without performance-based compensation. Additionally, we utilize the variation in scale and scope of external advisors' operations and show that advisors who care about their reputation, measured by a total pool of AUM and the number of client accounts managed, engage in significantly lower risk-shifting. We also confirm that our main results are robust to the use of alternative holdings-based measures of risk-shifting and to other empirical specifications.

Next, we consider the possibility that the fund's outsourcing status might be endogenous to its risk choice. To address this issue, we use an instrumental variable (IV) approach to establish a causal relation between outsourcing and mid-year risk-shifting. Following Chen et al. (2013), we instrument for a fund's outsourcing status based on the number of funds a family offered at its inception, controlling for family size. The idea is that fund complexes have a limited span of control, and as they offer more funds, they reach the capacity constraint and are more likely to outsource the management. Results from our IV approach confirm our earlier findings as we continue to find higher risk-shifting in outsourced funds. To further examine the causal effect of a fund's management status on its risk choice, we match outsourced funds (treated) to funds managed in-house (control) on observable characteristics that plausibly affect the funds' assignment to either one of these two groups. When we assess the difference between the two groups, we find that outsourcing status, along with mid-year fund performance, has a causal effect on the risk-shifting decision. Additionally, we document that the underperformance (11 bps per quarter) of outsourced mutual funds, on average, can be explained by those funds that engage in excessive conditional risk-shifting.

Finally, we test the efficacy of alternative mechanisms that help align incentives in incomplete contracting environments. More specifically, we test whether the three arrangements, *co-branding*, *co-location*, and *co-management*, have any moderating effect on the intrinsic risk-shifting behavior of the outsourced advisor. Over two-thirds of our sample uses at least one of these three mechanisms. Among these, co-branding and co-location reduce risk-shifting unconditionally, while the mitigating effect of co-management is concentrated in periods when outsourced funds underperform. While it does not fully eliminate the agency friction, we find that when the fund complex takes at least one of these additional measures, there is a 62% decrease, on average, in the level of risk-shifting. The existence of these mitigating factors helps explain why the use of external advisors is still increasing, even though the average outsourced fund is underperforming.[2]

Our paper makes several contributions to the literature. First, in the context of outsourcing, we identify a new incentive for external advisors to engage in conditional risk-taking: contract retention. This mechanism is conceptually distinct from prior literature that focuses on flow-based (e.g., Brown et al. (1996)) or performance-based incentives (e.g., Lee et al. (2019)). Unlike portfolio managers whose compensation is often explicitly tied to short-term performance, external advisors typically earn asset-based fees and face a binary outcome: contract renewal or termination, depending on annual fund performance. This creates a convexity in their payoff structure, where the marginal benefit of increasing volatility peaks when fund performance is close to the benchmark.

While we are not the first to link employment risk with risk-shifting, our setting is distinct in important ways. For instance, in Kempf et al. (2009), employment risk is balanced against compensation incentives, and managers often reduce risk even under poor mid-year performance, when job loss is the dominant concern. Importantly, the managers in their study operate within the boundaries of the fund family, where monitoring and alternative perfor-

[2]These results complement the findings of Moreno, Rodriguez, and Zambrana (2018) who document that similar contractual arrangements can protect investors from potential underperformance.

mance metrics can temper extreme behavior. By contrast, outsourced advisors in our setting face much sharper convexity in their payoff: termination of the advisory contract is more sensitive to performance, and weaker monitoring due to firm boundaries limits the principal's ability to intervene. As a result, retention incentives dominate, and outsourced advisors near the benchmark have a strong motivation to increase risk—regardless of the portfolio manager's own compensation structure. Our empirical results confirm this explanation and help us separate employment-driven risk-shifting from performance- or flow-motivated behavior.

Second, we shed new light on the outsourcing literature that investigates the various aspects of contract design. It is well understood that the presence of firm boundaries in outsourcing arrangements creates agency frictions. Chuprinin et al. (2015) showcase an example of such a friction and show that international outsourced advisors, who simultaneously manage their own fund(s) (side-by-side management), tend to favor their own fund(s) in allocations of initial public offering and use of privileged information and rely on the outsourced fund to support abnormal cross-trading activities during times of liquidity needs. Chen et al. (2013) suggest offering high-powered incentive contracts as a solution. However, we demonstrate that this contract is still incomplete and show that some fund families, perhaps aware of frictions, adopt costly organizational mechanisms to "complete" these contracts and mitigate agency problems. Moreno et al. (2018) also argue that specific contractual arrangements can mitigate outsourcing-related agency conflicts and diminish fund underperformance. Our work complements their findings by identifying an important mechanism behind underperformance—excessive conditional risk-shifting—and empirically validating how specific arrangements are effective. We document how co-branding and co-location reduce risk-shifting unconditionally, while co-management attenuates risk-shifting specifically when outsourced funds underperform. To our knowledge, we are the first to quantify the efficacy of these arrangements in directly moderating risk-taking behavior, providing a possible explanation for why outsourcing remains prevalent despite the average underperformance.

Finally, our study contributes to the broader literature on the contractual structures that shape fund management outcomes. The return an investor receives is the result of a complex chain of delegation. This process involves multiple parties—such as fund families, trustees, investment advisors, and portfolio managers—with each link in the chain governed by a separate contractual arrangement. While we do not attempt to model the full dynamics across all these layers, our evidence highlights how incentive misalignments can emerge in unexpected ways within multi-layered contracting environments. For example, prior work (Lee et al. (2019), Ma et al. (2019), Evans et al. (2020), and Evans et al. (2024)) shows that portfolio manager compensation design significantly influences outcomes such as risk-taking, performance, and intra-family allocations. In contrast, we find that outsourced advisors often exhibit muted responses to performance-based incentives, regardless of how portfolio managers are compensated. These findings underscore the importance of adopting a holistic perspective, where contract design is evaluated not only at the individual level but also in terms of how incentive structures interact across layers, offering broader lessons for both theory and practice in delegated asset management.

2 Hypotheses development

In the U.S., a substantial portion of mutual funds is managed by advisors external to the fund family to which investors allocate their capital. These outsourced advisors are responsible for portfolio management and are compensated with a fixed fee or a small fraction of the AUM (see Elton et al. (2003)).[3] However, it is very uncommon for investment advisors to have performance-based compensation. We discuss this in greater detail in section IA.A of the internet appendix.

By definition, the outsourced advisors are outside the firm boundaries of the fund family. Therefore, given the difficulty in monitoring and coordinating tasks, Chen et al. (2013) argue that the optimal solution for the fund family is to offer a contract with high-powered incentives. They empirically verify their assertion by estimating the probability of fund closure conditional on the past 12 months' performance. An outsourced fund is 78% more likely to be closed after poor performance compared to in-house managed funds (see Chen et al. (2013, Table VIII)). In our sample, we find the incremental probability of an outsourced fund's closure after poor performance to be 60% higher than in-house funds. Arnold et al. (2025) also show that sub-adviser turnover decisions are driven by underperformance, which reinforces the notion that termination risk is a central disciplinary mechanism in outsourced advisory relationships. Their difference-in-differences analysis finds that replacing poorly performing sub-advisers improves funds' risk-adjusted returns and net flows.[4]

The regulations governing the hiring and firing of sub-advisors also facilitate the easy execution of high-powered incentive contracts. Section 15(a) of the Investment Company Act of 1940 distinguishes between appointment and termination: appointing a new adviser requires both board and shareholder approval, while termination does not. Rule 15a-4 fur-

[3] Generally, the regulation governing sub-advisors is the same as the regulation governing investment advisors. Therefore, sub-advisors are subject to Rule 205 of the Investment Advisers Act, which means they must comply with the regulations regarding performance-based fees, i.e., it has to be fulcrum-based, or the investor must be a "qualified client."

[4] In section IA.B of the internet appendix, we provide some anecdotal evidence that fund performance is an important consideration for contract termination.

ther allows interim advisory contracts (up to 150 days) without shareholder approval. More importantly, in practice, most fund families operate under a "manager of managers" exemptive order ("Proposed Rule 15a-5") issued by the Securities and Exchange Commission (SEC) that allows the fund family to hire, terminate, or materially amend sub-advisory agreements without shareholder approval, subject only to board oversight and ex-post disclosure via an information statement (Kirsch (2011)).

The risk of termination creates a highly convex payoff structure for outsourced advisors, as they earn nothing if their contract is terminated. Importantly, according to our estimation, each contract is highly valuable as more than 90% of the advisors have three advisory contracts or less. The convexity makes their payoff akin to holding a digital ("binary") call option on fund returns, where the benchmark return acts as the strike price. This is true even when the external advisor earns an AUM-based fee, as the winner-takes-all (convex) flow-performance relationship in equity mutual funds (e.g., Sirri and Tufano (1998)) ensures that funds near the middle of the benchmark-adjusted performance distribution do not experience material AUM gains. In section IA.C of the internet appendix, we show that the vega of a digital option peaks when the underlying asset's price is in the neighborhood of the strike price. Therefore, outsourced advisors have a strong incentive to maximize expected payoffs by increasing portfolio risk when the fund's benchmark-adjusted return hovers around zero. That agents with higher vega in their payoff employ riskier strategies aligns with Khorana (2001), who demonstrates that career concerns drive managers toward risk-shifting in fund portfolios when faced with the threat of replacement. Similarly, Bollen and Pool (2009) find hedge fund returns exhibit discontinuity around zero, as managers, to avoid career concerns or limit excessive capital withdrawal, often avoid reporting small losses, leading to a disproportionately low number of funds with slight losses compared to similar gains.

The incomplete contracting environment complicates efforts to prevent risk-shifting, as advisors' signals about future returns are non-verifiable, and, crucially, advisors have several tools at their disposal to manipulate portfolio risk. Huang et al. (2011, Sec 5) identify some of these methods, including altering cash balances, adjusting tracking error volatility, and increasing exposure to varied risk factors. The problem is magnified by the presence of firm boundaries, which weakens the effectiveness of traditional monitoring mechanisms. Therefore, we believe that the outsourced advisors who are close to their benchmark return have the motive, means, and opportunity to engage in strategic risk-shifting.

Hypothesis 1a. Conditional on the fund performance being close to the benchmark return, advisors of outsourced mutual funds increase their portfolio risk to minimize their employment risk, which in turn maximize their expected future payoff . (retention hypothesis)

The compensation contracts offered by investment advisors to portfolio managers—the employees responsible for day-to-day portfolio decisions—differ significantly from those offered by fund families to investment advisors (see Lee et al. (2019) and Ma et al. (2019)). Unlike investment advisors, portfolio managers often receive compensation tied asymmetrically to fund performance. In our sample, 73% of portfolio managers have bonus components linked to the upside of fund returns.

These asymmetric contracts protect managers from penalties when the fund underperforms its benchmark, creating incentives for risk-taking. Specifically, portfolio managers with asymmetric contracts are more likely to increase portfolio risk later in the year, especially when a fund's excess return relative to its benchmark hovers near zero (Lee et al. (2019)).

While all portfolio managers with performance contracts have both the motive and means to engage in risk-shifting, outsourced fund arrangements, where weaker monitoring is common due to firm boundaries, may offer even greater opportunities for such behavior.

However, outsourced fund advisors are typically small, "owner-manager" firms handling a minimal number of accounts.[5] In our sample, the median investment advisor has only one mutual fund in their advisory portfolio. This high dependence on retaining each advisory contract makes the marginal benefit of contract renewal very significant. Considering the *retention hypothesis* of risk-shifting, we expect outsourced funds—regardless of whether portfolio managers have performance-based contracts—to exhibit risk-shifting behavior based on mid-year performance.

*Hypothesis 1*b. *The incentive to retain the advisory contract (retention hypothesis) is binding for the outsourced advisor, regardless of the portfolio manager's explicit contractual incentives. Consequently, the contract type offered to portfolio managers has no incremental impact on the outsourced advisor's propensity to engage in risk-shifting.* (*nexus hypothesis*)

Although higher risk can correlate with higher returns, excessive risk-taking tends to be sub-optimal, leading to lower risk-adjusted returns. Huang et al. (2011) confirm that, on average, such sub-optimal increases in mutual fund portfolio risk result in fund underperformance. We empirically test this relation.

Hypothesis 2. Outsourced funds that engage in excessive risk-shifting have a lower risk-

[5] The following is the example description of Sycuan US value fund whose outsourced advisor is A.Q. Johnson & Co., Inc.: "Mr. Johnson owns all the outstanding shares of the A.Q. Johnson & Co, Inc. and therefore his compensation is largely based on the profits realized by the A.Q. Johnson & Co, Inc. for managing the Fund. He participates directly in all profits and losses of A.Q. Johnson, including the advisory fees paid by the Fund. There are no bonuses, deferred compensation or retirement plans associated with his service to the Fund." (https://www.sec.gov/Archives/edgar/data/1253771/000141304208000012/sycuan485bpos.htm)

adjusted return than other outsourced funds.

While explicit contractual clauses limiting risk-shifting may not be enforceable by third parties, such as courts, fund families have a strong incentive to curb risk-shifting, as it can lead to poor portfolio returns. Moreover, replacing the advisor ex-post is expensive due to search costs, relationship-building efforts, and the need for investor communication. Consequently, fund families are likely to take preemptive actions to mitigate risk-shifting. We identify three mechanisms from the literature that are likely effective in "completing" contracts.

Co-branding is a contractual arrangement in which a fund family collaborates with an external advisor to jointly market and manage a fund. Typically, this includes incorporating the outsourced advisor's name into the fund's title, leveraging the advisor's reputation to enhance the fund's appeal (e.g., Klein and Leffler (1981)). This approach not only capitalizes on the advisor's brand but also aligns the advisor's incentives with those of the fund family, as the external advisor bears reputational costs for poor performance or deviations from the prescribed strategy (see Moreno et al. (2018)).

Hypothesis 3a. *Risk-shifting in outsourced funds is diminished when the fund is co-branded.*

Hong et al. (2005) emphasize the role of geographic proximity in facilitating information transmission among professional investors. They find that mutual fund managers located in the same city are more likely to share information through word-of-mouth channels, leading to greater portfolio similarity compared to managers residing in different cities. Pool et al.

(2015) extend this insight by showing that portfolio overlap is significantly higher among fund managers who are not only in the same city but also in the same neighborhood. They further document that many managers who live in the same city share social networks, and they "frequently" or "sometimes" share investment ideas with other fund managers, including those from different fund families. These findings illustrate how geographic separation can increase the costs of governance and monitoring. Distance between the principal and the agent may reduce the scope for oversight and weaken informal information flows through social and professional networks (see Kang and Kim (2008) and Jensen et al. (2015)). Given that outsourced advisors operate outside the fund company's internal organizational structure, we expect that the physical distance between the fund company and the advisor will significantly hinder effective monitoring.

Hypothesis 3b. *Risk-shifting in outsourced funds is diminished by lower geographical proximity between the fund family and the advisor (co-located).*

Our sample includes many outsourced funds co-managed by multiple external advisors. Theory offers competing predictions about how co-management affects risk-shifting. On one hand, peer monitoring among co-managers can enhance productivity and curb excessive risk-taking (Kandel and Lazear (1992)), address the return disadvantage of sub-advised funds (Moreno et al. (2018)), broaden stock holdings, improve performance, and reduce illegal practices such as portfolio pumping (Patel and Sarkissian (2017); Patel and Sarkissian (2021)). On the other hand, co-managed funds typically adopt a decentralized, sleeve-based structure in which each sub-advisor independently manages a distinct portfolio segment. In such arrangements, the prerequisites for effective peer monitoring — shared information, mutual observability, and joint accountability — are largely absent. Drawing on Sah and Stiglitz (1988), Csaszar (2012) shows that funds with decentralized structures accept more "projects" and commit more errors of commission relative to centralized ones. Cross-firm boundaries further impede information sharing and weaken incentive alignment. Whether co-management mitigates or amplifies risk-shifting, therefore, depends critically on the registrant's structural choice.

This tension may be resolved by the degree of principal advisor involvement. Greater engagement by the principal advisor can limit risk-shifting by coordinating sub-advisors and preventing style conflicts (Dass et al. (2013); Broman et al. (2023)). However, such oversight is costly and unlikely to be uniform across funds. On balance, we predict:

Hypothesis 3c. *Risk-shifting in outsourced funds is diminished by the presence of multiple advisors (co-managed).*

3 Data and Summary Statistics

We construct our sample from several data sources. Our first source is the Morningstar Direct Mutual Fund database, which covers U.S. domestic equity mutual funds and includes mutual funds' name, style category, and benchmark. The benchmark is the self-designated index disclosed in each fund's prospectus. Our sample period begins in January 1999 and ends in December 2024. Data regarding the daily returns of benchmark portfolios also comes from Morningstar. We next match the Morningstar data to the Center for Research in Security Prices (CRSP) Mutual Fund database using the CUSIP number, ticker, or both. The CRSP

Mutual Fund database includes fund characteristics, net asset values (NAVs), and returns for each share class at a daily frequency. We use a name-matching algorithm for the remaining unmatched observations. We exclude index funds from the sample using their names and CRSP index fund identifiers. A share class should have at least 200 daily return observations in a year to be included in the sample for the given year.

For funds with multiple share classes, we aggregate across the different share classes to compute fund-level variables using MFLINKS data.[6] More specifically, we calculate the sum of assets across all share classes and compute the value-weighted average of fund characteristics across share classes. We use the Thomson Reuters Mutual Fund database to compute holding-based measures.

We use N-SAR filings and the new N-CEN fillings (post-2017) to collect information on fund advisors and sub-advisors. The information collected includes their name, address, fund family name, and SEC advisor number. We then look up the Form ADV, filed by investment advisory firms, to check the affiliation of the advisor with the fund registrant and that of the sub-advisor(s) with the registrant and the advisor. If the names match or if our review of the Form ADV shows affiliation, we identify the fund as managed in-house; otherwise, we identify it as outsourced. Funds seldom have multiple advisors, but conditional on being sub-advised, it is common that they have multiple sub-advisors. Additionally, following Chen et al. (2013), a fund is considered outsourced if at least one of its advisors is external to the fund family. Note, by our definition, not all sub-advised funds are outsourced. In addition, the lack of a sub-advisor does not preclude it from being outsourced, as the principal advisor

[6] Despite the use of the MFLINKS file, some share classes are still not mapped to any identifier. For these remaining observations, we use the CRSP portfolio identifier crsp_cl_grp to aggregate the different share classes.

could be unaffiliated with the fund family.

Mutual funds disclose the compensation structure of the fund manager(s) in the Statement of Additional Information (SAI). We retrieve the SAI of each fund in our sample from the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database and classify the contracts into various categories. More precisely, we record whether an incentive bonus exists and whether the bonus is tied to the fund's investment performance. In addition, by reading the SAI, we can identify the compensation structure of sub-advisors if fund management is outsourced.

Table 1 provides a summary of the key variables. The average in-house fund is 13.4 years old, while the average outsourced fund is 8.9 years old. The expense ratio charged by the two fund types is very similar. Outsourced funds are typically smaller. On average, in-house funds are roughly two times larger than their counterparts. Consequently, the proportion of total industry AUM managed by outsourced funds is relatively modest. Over the past two decades, the number of outsourced funds has steadily increased. By the end of our sample period, over 30% of funds had delegated portfolio management to external advisors.

Furthermore, to assess the significance of these advisory contracts, we plot the distribution of the average number of mutual funds managed annually by each external advisor. For each advisor, this value represents the time-series average of the number of funds they manage over our sample period. Figure 1 plots the percentage of advisors in the six non-equal bins. Clearly, bin '1' includes more than 50% of the sample of advisors, indicating that the median advisor manages no more than one outsourced fund. Additionally, more than 90 percent of advisors manage no more than three funds.

4 Outsourcing and Mutual Fund Risk-Shifting

4.1 Variable construction

We quantify risk-shifting by comparing the relative volatility or the volatility of the tracking error. Given that fund performance is judged relative to a benchmark and considering the importance of asymmetric performance bonuses in portfolio manager compensation, if managers attempt to beat the benchmark by increasing portfolio risk, they have to increase the risk of the portfolio relative to the benchmark. To capture changes in portfolio volatility, following Lee et al. (2019), we define the risk adjustment ratio RAR as follows:

$$RAR_{j,t} = \frac{\sigma_2(r_{j,t} - b_{j,t})}{\sigma_1(r_{j,t} - b_{j,t})} \tag{1}$$

where $\sigma_1(r_{j,t} - b_{j,t})$ and $\sigma_2(r_{j,t} - b_{j,t})$ are the standard deviations of fund j's return over the benchmark return for the first six months and the second six months of the year, respectively. These standard deviations are computed using daily returns and hence provide a much more reliable estimate of the manager's actions regarding fund volatility. We believe that using higher-frequency data (daily) to measure portfolio risk choices helps alleviate concerns about unobserved managerial actions within the quarter (e.g., Kacperczyk et al. (2008), and Elton et al. (2010)). In addition, fund return data is more complete, and using it helps avoid sample attrition due to missing holdings or variation in fund reporting frequencies. Chen et al. (2018) also strongly advocate for using such a return-based risk measure. However, for completeness, we also estimate a holdings-based measure of risk-shifting (e.g., Kempf et al. (2009)) and present those results in the internet appendix.

We compute the excess return ($Exret$) of each fund over its respective benchmark as the difference between the compounded daily returns of the fund and its benchmark for the duration of the first six months. After computing $Exret$, we measure the distance of the fund's return from its benchmark return as the square of $Exret$, giving equal importance to returns above and below the benchmark. Note RAR is not the ratio of standard deviations first analyzed by Brown et al. (1996). Instead, this is the ratio of tracking errors relative to the fund's self-selected benchmark. In Figure 2, we partition the excess return distribution and plot the average RAR values for the different regions by fund type. This simple univariate plot showcases one of the central insights of our paper. All fund types, on average, increase their portfolio risk the most when their mid-year performance is close to the benchmark. However, in that interval, the outsourced funds (solid line) increase their portfolio risk much more than the in-house managed funds (dotted line).

4.2 Panel regressions

4.2.1 Retention hypothesis

We now examine the risk-shifting behavior of in-house and outsourced funds using a regression approach. Following Lee et al. (2019), we begin by estimating the following pooled ordinary least square (OLS) model:

$$
\begin{aligned}
RAR_{j,t} = a_t + c_1 Distance_{j,t} + c_2 Distance_{j,t} * I_{Outsourced} \\
+ c_3 I_{Outsourced} + c_4 Controls_{j,t} + e_{j,t}. \qquad (2)
\end{aligned}
$$

The dependent variable, $RAR_{j,t}$, is the change in fund risk relative to a benchmark between the first and second halves of year t. The key explanatory variable in Equation (2), $Distance$, is given as the square of the excess return ($Exret$) and captures how far the excess return lies from zero. The additional control variables are the expense ratio ($Exp\,ratio$), the turnover ratio ($Turn\,ratio$), the percentage of flows into the fund during the first six months of the year ($Flows$), the log of the number of years since fund inception ($Log\,age$), the compounded return of the fund for the previous calendar year ($PastReturn$), and the log of total AUM ($Log\,size$). These variables are all evaluated at the beginning of the calendar year. Kempf et al. (2009) argue that managerial risk-taking changes as a function of the state of the economy. To account for this temporal variation, all of the specifications include time-fixed effects.

Most mutual fund managers are compensated based on performance relative to a benchmark, and these contracts are typically asymmetric: managers are not penalized for underperformance, which incentivizes greater risk-taking. Lee et al. (2019) show that, consistent with this asymmetry, risk-shifting in the second half of the year is inversely related to the distance between portfolio return and the benchmark return. So, we expect the coefficient c_1 to be negative and statistically different from zero. $I_{Outsourced}$ is a dummy variable which takes the value of one if the fund is outsourced and zero otherwise. The *retention hypothesis* of risk-shifting predicts that outsourced funds, if anything, would strategically take on more risk as the trade-offs from retaining or losing the advisory contract are very large. Therefore, we expect the interaction coefficient of $Distance$ and $I_{Outsourced}$, c_2, to have a negative sign.

Table 2 presents the results from the pooled OLS regression, with standard errors clustered by fund to account for correlation in the error terms. In column (I), the negative

Distance coefficient confirms the main finding of Lee et al. (2019) that risk-shifting is strongest in the region in which the fund's return is close to the benchmark's return. In Column (II), we examine the key hypothesis of this paper by adding the interaction term between *Distance* and management outsourcing dummy ($I_{outsourced}$). The negative coefficient on the interaction term indicates that the outsourced funds, when compared to the in-house funds, strategically increase portfolio risk more in the second half of the year to maximize the value of their payoff. Interestingly, the magnitude of the coefficient on the interaction term is almost as large as the point estimate on *Distance*. This suggests that the outsourced funds risk-shift almost twice as much as in-house managed funds. The magnitude of the reported coefficients is dampened by the inclusion of the COVID-19 pandemic year, 2020, which had one of the lowest *RARs* in our sample. For robustness, in section IA.D of the internet appendix, we also provide results excluding this period. The evidence supports the interpretation that the attenuation is concentrated only in the initial pandemic year rather than reflecting a persistent structural change.

In Columns (III) and (IV) of Table 2, we present the results from a quantile regression model (at the median) with bootstrapped standard errors as an alternative to the OLS specification. The robustness of quantile regression to any potential outliers merits its use. The coefficient of *Distance* is statistically significant and negative, suggesting that for the median manager, the portfolio risk in the second half of the year will decrease as the portfolio's return deviates from the benchmark's return. More importantly, the coefficient on the interaction term is still negative and highly significant. Also, consistent with the OLS results, the magnitude of the interaction term is similar to the main effect. These results clearly establish that managers of outsourced firms strategically engage in incremental risk-shifting.

To further highlight variation in managers' risk-shifting responses, we estimate a piecewise linear specification. In Section IA.E of the internet appendix, we partition the support of the performance distribution into four regions and allow for region-specific slopes. The results in Table IA.2 reinforce the interpretation that outsourced managers respond strategically to convex incentive structures: they do not uniformly increase risk, but instead shift risk selectively in regions where the marginal value of doing so is greatest.

4.2.2 Nexus hypothesis

We next evaluate whether the *nexus hypothesis* of risk-shifting, which relies on the explicit compensation incentive of portfolio managers and weaker monitoring due to the presence of firm boundaries, plays any role in explaining the above results. Note that the two incentives, advisory contract retention and compensation maximization, are not mutually exclusive. To test this hypothesis, we hand-collect information on the portfolio manager compensation structure from 2005 to 2024 and capture the cross-sectional variation in compensation by segmenting our sample into two contract types. The first type is a group of funds that clearly state that portfolio manager compensation is not tied to fund performance. The second type includes funds whose managers are paid based on fund performance. Mostly, the second group consists of funds that clearly specify that the manager's compensation is based on performance relative to a specific benchmark. $I_{performance}$ is a dummy variable that takes the value of one when the manager has a performance-based contract and zero otherwise. Consistent with Lee et al. (2019), about 27 percent of our sample do not have performance-based compensation.

In columns (V) and (VI) of Table 2, we focus on the subsample of outsourced and in-house funds, respectively. The interaction between *Distance* and $I_{performance}$ is our main variable of interest as it helps ascertain whether explicit compensation incentives are associated with incremental risk-shifting decisions. For the outsourced sample, the coefficient on the interaction term is statistically indistinguishable from zero. In other words, their explicit risk-shifting incentives arising from the compensation contracts do not dictate the portfolio risk choice. On the other hand, in column (VI), managers of the in-house managed funds, who don't face high-powered incentive contracts and the related employment risk, appear to maximize the vega of the option explicit in their compensation contract. The coefficient on the interaction term is negative, suggesting that those with performance-based incentives engage in more strategic mid-year risk-shifting.

Overall, our results support the hypothesis that the implicit optionality introduced by the high-powered incentive contract has a significant impact on the strategic actions of external advisors. In the case of an outsourced advisor, the motivation to retain the contract is more binding than the incentive to exploit the convexity in the compensation contract.

4.3 Causal effect of outsourcing

Our results thus far do not claim a causal impact of outsourcing on fund risk-shifting. It is possible, although unlikely, that the fund family's decision to outsource the fund management is endogenous to the portfolio manager's decision to increase the portfolio risk. If true, this could bias the coefficient estimates. Below, we present two different approaches to get around the potential endogeneity and establish that, indeed, the outsourcing status of the fund has a causal impact on the strategic risk-taking.

4.3.1 Instrumental variables analysis

We begin with the instrumental variable methodology. Our approach is well motivated by Chen et al. (2013), who propose an instrument for whether a fund is outsourced based on the number of other funds that the fund family offered at the time of inception of the fund ($LogFamFunds_{i,0}$), controlling for family asset size. The basic idea behind this approach is that as fund families increase their product offerings relative to the family size, they are more likely to hit the capacity constraints and hire external advisors.

We begin our empirical test by running the first-stage regression. We intend to establish that the number of funds in the fund family at the time of inception is highly correlated with the outsourcing status of the fund. Given that the unit of analysis in the second stage is at the fund-year level, we run the following specification using a similar level of data:

$$
\begin{aligned}
Pr(Outsourced_{i,t} = 1) = \Gamma(&\mu + \phi LogFamFunds_{i,0} + \kappa FamSizeDummies_{i,0} \\
&+ \eta LogFamFunds_{i,t} + \nu LogFamSize_{i,t} + \gamma X_{i,t} + \delta I_t) \qquad (3)
\end{aligned}
$$

where $Outsourced_{i,t}$ is a dummy variable that equals one if fund i is outsourced in year t and zero otherwise, $LogFamFunds_{i,0}$ is the natural log of one plus the number of funds in the family at the inception of the fund, and $LogFamFunds_{i,t}$ is the natural log of one plus the number of funds in the family in year t. The subscript zero is used to denote the time when the fund was started. In addition, we include percentile dummies for the size of the fund family when the fund was launched ($FamSizeDummies_{i,0}$), and the natural log of family size (AUM) for year t ($LogFamSize_{i,t}$). Other fund-level control variables ($X_{i,t}$) are also included along with the dummies for each year in our sample. We use the conditional logit estimator to precisely account for unobserved time-invariant heterogeneity and estimate the conditional probability that the fund will be outsourced. $\Gamma(.)$ in Equation (3) represents the logistic distribution function.

The results of the first-stage regression are presented in Table 3. In column (I), the positive coefficient on $LogFamFunds_{i,0}$ confirms our earlier expectation and is consistent with what Chen et al. (2013) also find. Families that have to manage a higher number of funds do outsource more. In fact, this is not just true of the number of funds at inception but, based on the coefficient of $LogFamFunds_{i,t}$, also true of the number of funds currently managed. Furthermore, the statistical significance of the coefficient estimate rules out any concerns regarding the suitability of the instrument.

For $LogFamFunds_{i,0}$ to be a valid instrument, it must also satisfy the exclusion restriction—that is, it must affect $RAR_{i,t}$ only through the fund's outsourcing status (the endogenous regressor), with no direct influence. It is unlikely that a fund family's past decision (i.e., $LogFamFunds_{i,0}$) would directly influence a portfolio manager's incremental risk-taking today. However, it is possible that $LogFamFunds_{i,0}$ proxies for deeper family-level organizational design choices—such as latent monitoring structures—that may affect portfolio oversight regardless of outsourcing status.[7] While the exclusion restriction is fundamentally untestable, to strengthen the validity of our instrument, we perform a falsification test using a fund characteristic plausibly associated with monitoring but unlikely to be affected by the outsourcing decision: derivative use. Specifically, we regress a fund's use of derivatives on

[7] We thank an anonymous referee for bringing this to our attention.

the instrument, controlling for a rich set of fund characteristics. If the instrument had a direct effect on risk-taking through this alternative channel, we would expect a statistically significant relationship between these variables.

We obtain data on derivative use from NSAR filings, where funds report whether they use financial derivatives such as options or futures. Since responses are binary ("Yes" or "No"), we choose logistic regression design. We estimate the same model as in Equation (3), with $Derivative\ Use_{i,t}$ as the dependent variable—an indicator equal to one if the fund uses any derivatives (options, futures, or both), and zero otherwise. These results are reported in column (II) of Table 3. Some observations are lost due to a lack of within-family variation in derivative use, but overall we find no statistically significant relationship between $LogFamFunds_{i,0}$ and derivative use.

We also leverage additional information from the NSAR forms to construct a broader indicator variable, capturing whether a fund uses derivatives, engages in short selling, buys on margin, or invests in restricted shares. This extended outcome is also binary and serves as the dependent variable in column (III) of Table 3. Again, we find no evidence of a significant association. These falsification tests bolster our interpretation that the past number of funds in a family affects risk-shifting only through outsourcing decisions. That is, fund families with more funds at inception do not appear to differ systematically in their approach to risk management or future risk-taking, except through their decision to outsource.

After establishing the first-stage regression result, we move on to the next step by implementing a two-stage residual inclusion (2SRI) approach. This is the ideal approach since we use a nonlinear estimation in the previous stage. We use the following specification for the second stage:

$$
\begin{aligned}
RAR_{i,t} = \mu + \alpha Distance_{i,t} + \beta Distance_{i,t} * I_{Outsourced_{i,t}} + \varphi I_{Outsourced_{i,t}} \\
+ \kappa FamSizeDummies_{i,0} + \eta LogFamFunds_{i,t} + \theta LogFamSize_{i,t} \\
+ \gamma X_{i,t} + \delta I_t + \psi FirstStageResiduals_{i,t} + \varepsilon_{i,t},
\end{aligned} \tag{4}
$$

where $FirstStageResiduals$ is the residuals from the estimation of Equation (3). We include all explanatory variables from the first stage in our second stage regression except for our instrument, $LogFamFunds_{i,0}$.

Table 4 reports the second-stage results from the 2SRI approach. After controlling for the first-stage residuals, the coefficient on $Distance$ remains negative and statistically significant, as does its interaction with the outsourcing indicator, consistent with our baseline findings. Importantly, the magnitude of these coefficients remains largely unchanged when instrumenting for outsourcing. The coefficients on the $FirstStageResiduals$ and the interaction with $Distance$ are statistically insignificant, suggesting that unobserved factors influencing outsourcing have a limited impact on funds' risk-taking decisions, thereby alleviating endogeneity concerns. Overall, the 2SRI estimates support a causal effect of outsourcing on risk-shifting behavior.

4.3.2 Matching analysis

To strengthen the causal interpretation and overcome any selection issues, we use a matching approach and pair each outsourced fund (treated) to an observationally similar non-outsourced fund (control), based on size, age, expense ratio, turnover, flows, and prior-year returns. We further require that the treated fund and the matched control fund are in the exact same year and have the same fund style, as this creates a more precise match. Figure IA.1 in section IA.F of the internet appendix demonstrates that the matching procedure achieves strong covariate balance, with the two groups becoming highly similar along observable dimensions. While we cannot rule out the possibility that treated funds are different from controls along some unobserved dimensions, we can reasonably assume that, conditional on these important observable characteristics, assignments to the treatment and control groups are random. Thus, the only difference between the two groups is the outsourcing status.

We repeat the earlier regression analysis on the matched sample to test whether the treated (outsourced) funds in fact shift risk significantly more. In column (I) of the Table 5, we use a greedy matching algorithm to match the treated with the control sample. In column (II), we use an optimal matching algorithm (nearest-neighbors) with replacement. As in previous regression results, the coefficient on the interaction term is negative and statistically significant in the greedy matching analysis. The statistical significance of the coefficient from the optimal matching analysis, however, is somewhat weaker. Overall, these results confirm our hypothesis that, on average, outsourcing status, along with mid-year performance, has a causal effect on the mutual fund risk-shifting decision.

4.3.3 Employment risk explaining the variation in risk-shifting

In this section, we use the variation in the scale and scope of external advisors' operations to highlight further the role of the *retention hypothesi*s on mid-year risk-shifting. Debaere and Evans (2015) document that the limited access to mutual fund investment dollars through marketing and distribution channels leads the outsourced advisors to manage an external fund rather than starting their own fund. The limited visibility in the retail space (i.e., due to a specialty in managing institutional accounts) may incentivize external advisors to manage funds through sub-advising for large fund families. This observation motivates us to examine the extent of risk-shifting across the different types of external advisors. If the external advisor already enjoys a superior reputation in the management outsourcing industry, maintaining a less volatile track record will create a positive spillover effect in attracting fund flows (Nanda et al. (2004)). Furthermore, this can lead to a reputation-stretching strategy in terms of future outsourcing arrangements (Chen and Lai (2010)).

We introduce two variables to capture the variation in advisor attributes. First, $AdvSize$ is defined as the log demeaned total AUM of the advisor. Second, we create a dummy variable, $I_{AdvCount}$, which takes the value of one when the total number of funds under the management of the advisor is greater than the median number and zero otherwise. Our expectation is that advisors who have higher AUM and advisors who manage a higher number of funds should care less about losing an advising contract as the marginal utility of the payoff from that contract is lower to them. In addition, such advisors would also care more about reputation building and maintaining a smooth track record.

Columns (I) and (II) of Table 6 report estimates of the three-way interactions, ($Distance * I_{outsourced} * AdvSize$) and ($Distance * I_{outsourced} * I_{AdvCount}$), which capture how risk-shifting varies with advisor characteristics. The results indicate that more established advisors engage in less risk-shifting. The count-based measure of advisor scale yields more robust results than the AUM-based measure. This contrast is economically intuitive, as the number of accounts an advisor manages more directly captures the diversification of their business across clients, thereby weakening the retention incentive for that contract. Given the skewness in fund sizes, advisors with large AUM, by contrast, may concentrate their aggregate AUM in a small number of relationships, making the count measure a cleaner proxy for the marginal cost of losing one contract. Overall, this evidence provides strong support for the retention hypothesis, as proxies for lower employment risk and reputational concerns reduce the incentive to take on excessive risk.

4.4 Outsourcing, risk-shifting, and fund performance

Thus far, we have demonstrated that advisors strategically choose to manipulate portfolio risk as it is optimal from their perspective of maximizing payoff. However, excessive risk-taking can be suboptimal for the fund investors. Huang et al. (2011) show that, on average, mutual funds that increase risk perform worse than funds that keep risk levels stable over time. Therefore, we now test whether increased risk-shifting is related to the poor performance of outsourced mutual funds.

For each quarter, we compute the fund's quarterly alpha by compounding the monthly alpha. The monthly alphas are computed using factor betas estimated over a rolling 12-month window. We estimate the alpha using both the Fama-French three-factor and the Carhart four-factor models. We closely follow the specification used in Chen et al. (2013) and first evaluate how the fund's outsourcing status and other characteristics are related to its next quarter's performance. Table 7 reports the estimates from Fama-Macbeth regression where the standard errors are adjusted for serial correlation using the Newey-West approach with lags of order three.

Columns (I) and (III) present the results for the three-factor and the four-factor models, respectively. Consistent with previous literature, funds that performed well over the last twelve months continue to outperform in the next quarter. Also, funds that have a higher expense ratio tend to have lower alphas. However, importantly, consistent with the findings in Chen et al. (2013), we find that outsourced funds underperform in-house funds by about 6.6 basis points a quarter. To test the impact of risk-shifting on the performance of outsourced funds, we introduce a new variable, $HighRAR$. This dummy variable takes the value of one if the fund's quarterly RAR is in the top quintile of the cross-sectional RAR distribution. The variable $HighRAR$ takes the value of zero otherwise. In columns (II) and (IV), when we interact the $HighRAR$ dummy variable with the outsourcing dummy variable, we find that the effect of outsourcing on performance diminishes both statistically and economically. Instead, the interaction term now accounts for most, but not all, of the underperformance. This is consistent with the interpretation that excessive risk-shifting is one of the primary drivers of outsourced fund underperformance, while a modest residual performance gap may reflect other frictions associated with the outsourcing arrangement. Overall, the economic magnitude of underperformance is quite significant as these funds underperform the peer group, funds that are managed in-house and do not risk-shift excessively, by 15.2 (11.4) basis points per quarter when using the three-factor (four-factor) evaluation model.

5 Management Arrangement and Risk-Shifting

Our analysis reveals that the presence of firm boundaries, combined with the implicit optionality in the payoff structures of outsourced funds, often leads to suboptimal portfolio choices and poor fund performance. The severity of the distortion in risk choice can be both accentuated and mitigated in the presence of various contractual features. As a next step, we leverage variation in the outsourcing environment to examine whether proposed contractual arrangements are statistically associated with attenuated principal-agent frictions.

5.1 Co-branding of fund name

Co-branding is a form of contractual arrangement where the fund family partners with an outside advisor to market and manage the fund jointly. A typical arrangement is one where the name of the outsourced advisor is included in the name of the fund. Often, this is done to extract value from the reputation of the external advisor. An advisor's reputation could be essential to their identity, influence future capital raising, or both. In addition, such a mechanism acts as an effective tool to align the incentive of the external advisor to that of the fund family, as there are reputation costs borne by the external advisor for poor performance or for any deviation from the prescribed strategy (see Klein and Leffler (1981) and Moreno et al. (2018)). Therefore, we expect co-branded funds to engage in significantly less risk-shifting.

To test hypothesis 3a, we create a new dummy variable, $I_{\{Co-brand\}}$, that takes the value of one if the fund is co-branded and zero otherwise. The fund is classified as co-branded when at least part of the external advisor's name is included in the fund name. In our sample, 36% of the outsourced funds are co-branded.

In Table 8, the point estimate on *Distance* (-2.875) clearly indicates that outsourced funds risk-shift. However, importantly, the coefficient on the two-way interaction term, $Distance{*}I_{\{Co-brand\}}$, is positive and statistically significant. The magnitude of the interaction coefficient suggests that a co-branded fund engages in 63% less risk-shifting than the average outsourced fund. Overall, this is consistent with our hypothesis that co-branding, as a contractual mechanism, mitigates risk-shifting incentives.

5.2 Co-location of fund advisor and registrant

The impact of geography on agency costs is fairly well-established in the literature (see Kang and Kim (2008) and Jensen et al. (2015)). Hypothesis 3b relates to this idea and argues that when fund families outsource to geographically proximate advisors, the extent of risk-shifting is attenuated. To empirically test this, we compute the geospatial distance ($GeoDistance$) between the legal addresses of the fund registrant and the advisor. When there are multiple advisors, we use the distance to the closest advisor to measure the spatial distance.

Using our empirical model above, we test whether the geospatial distance exacerbates risk-shifting among outsourced funds. To make the interpretation of our analysis easier, we define two dummy variables, $I_{\{High-GeoDistance\}}$ and $I_{\{In-State\}}$. First, $I_{\{High-GeoDistance\}}$ takes the value of one if the distance between the registrant and the fund advisor is above the median and zero otherwise. In addition to using the distance, we create the second dummy variable $I_{\{In-State\}}$, which takes the value one if the registrant and the fund advisor are located in the same state. Approximately, 26% of the outsourced funds have their external advisor in the same U.S. state as the fund is registered.

Consistent with our expectations, in Table 9, we find that geographical proximity also matters. While we observe that outsourced funds risk-shift, the negative coefficient on the two-way interaction term in column (I) shows that when fund advisors, the agent, are located farther than the median distance from the fund registrant, the principal, they strategically take more risk.[8] Results in column (II) are also consistent with this finding. When the advisors are located out of state, the extent of the risk-shifting is heightened.

While our data do not allow us to isolate the precise mechanism through which co-location improves monitoring, we view it as one of several heterogeneous channels through which fund families can maintain control over outsourced advisors. Effective monitoring can also emerge from other organizational features. We test one such feature: the presence of a "cohort fund"—an in-house fund operated by the fund family that shares the same investment style as the outsourced fund. We hypothesize that the presence of a style cohort reduces the importance of geographic proximity by providing fund families with a direct internal benchmark for evaluating the relative performance of their outsourced advisors. In column (III) of Table 9, we introduce a new dummy variable, $I_{\{StyleCohort\}}$, which equals one if, for a given outsourced fund, there exists another fund in the same family, in the same year, with the same CRSP style code, but managed internally. While our main findings remain robust, the three-way interaction term is positive, consistent with the idea that the presence of style cohort funds mitigates the need for the potential monitoring via co-location. However, the coefficient is not statistically significant. Although we cannot reject the null, we emphasize that co-location itself is not a direct monitoring mechanism. Rather, we interpret it as a proxy for a broader capacity for oversight—one that operates by facilitating communication and enabling informal supervision through social and professional networks (Pool et al. (2015)).

[8]Note that we implicitly assume that the advisors of outsourced funds are operating from their registered address.

5.3 Co-management by fund advisors

Co-management describes an arrangement in which a fund is managed by multiple external advisors. Its effect on risk-shifting is theoretically ambiguous. Besides the expected direct influence through peer monitoring, co-management arrangements enable broader investment mandates, stimulate greater idea generation, and enhance informational diversity, leading to more novel or liquid stock positions, which could reduce portfolio volatility through diversification effects.[9] However, in practice, this decentralized, sleeve-based structure under which multiple subadvisors operate does not foster peer monitoring of risk-shifting (Csaszar (2012)). Under normal operating conditions, each subadvisor's portfolio decisions are not routinely visible to the others. While the principal fund advisor must monitor the overall fund-level portfolio composition and harmonize strategies across subadvisors (Broman et al. (2023)), such multi-party coordination and active intervention are costly (Dass et al. (2013)) and are typically absent in co-managed funds on a day-to-day basis. Therefore, consistent with our discussion of Hypothesis 3c, the mitigating effect of co-management is contingent on the degree of principal advisor involvement. We identify one such scenario when the gains from active advisor intervention exceed the costs of collective action: fund underperformance. We begin our analysis by documenting differences in portfolio composition between single- and co-managed funds before turning to the central question of mitigating risk-shifting. Subsequently, we test whether co-managed funds unconditionally engage in lower risk-shifting and, if not, whether the threat of fund underperformance generates the expected gains from co-management.

Using the mutual fund holdings data, we introduce three new metrics: $NewStocks$,

[9] We thank an anonymous referee for pointing this out.

$UniqueStocks$, and $RareStocks$. $NewStocks$ is defined as the number of stocks held by a fund in a given quarter that were not held by the same fund at any time during the preceding year. $UniqueStocks$ counts the number of stocks held by a fund that are not held by any other funds within the same style category in the same quarter. $RareStocks$ measures the number of stocks held by a fund that are held by no more than 10% of funds in its style category. Additionally, following the method outlined in Kacperczyk et al. (2005), we compute the Industry Concentration Index (ICI) for each fund. To measure the level of fund diversification, we follow the methodology proposed by Pástor et al. (2020). A portfolio is considered well-diversified if it holds a substantial fraction of the benchmark's stocks ($Coverage$) and if its portfolio weights are close to market capitalization weights ($Balance$). The benchmark portfolio is constructed as the union of all stocks held by funds within the same style category in a given quarter. Following Pástor et al. (2020, equation 23), $Diversification$ is computed as the product of $Coverage$, and $Balance$.

We conduct a series of two-sample t-tests (assuming unequal variances) on a range of portfolio characteristics. The results in panel A of Table 10 indicate that co-managed funds hold new, unique, and rare stocks significantly more relative to their single-managed counterparts. These findings support the idea that co-management is associated with greater idea generation or informational diversity, leading to more novel and less commonly held portfolio positions. We also find that co-managed funds exhibit significantly lower ICI values, suggesting broader sectoral diversification and less emphasis on concentrated industry bets. Moreover, co-managed funds display significantly higher overall diversification, with the difference driven primarily by substantially greater $Coverage$—that is, co-managed funds tend to hold a larger fraction of the benchmark universe.

While the portfolio differences above confirm broader investment mandates and informational diversity, they do not, by themselves, imply risk-shifting is mitigated. We now test whether risk-shifting diminishes in the presence of multiple advisors and report our results in panel B of Table 10. About 22% of the outsourced funds in our sample have more than one external advisor. Column (I) presents the results of our baseline regression, where $I_{\{advisor>1\}}$ is a dummy variable with a value of one when the number of external fund advisors is greater than one. Statistically, the coefficient of our key variable of interest, the interaction between $Distance$ and $I_{\{advisor>1\}}$ is no different than zero. Therefore, we fail to reject the null hypothesis (Hypothesis 3c) that risk-shifting in co-managed funds is unconditionally no different from that in single-managed funds. We now test whether the benefits of co-management materialize under specific conditions, previously identified, where the gains from coordination exceed the costs. To test this hypothesis, we create a dummy variable, $I_{\{Below\}}$, which takes the value of one if the fund return is below the benchmark and zero otherwise. In column (II), when we include $I_{\{Below\}}$ to our earlier specification, we observe the varied effects of co-management on the different regions of the performance distribution. Importantly, when outsourced funds are underperforming, the heightened engagement of the principal advisor and the peer monitoring appear to constrain the risk-shifting behavior in co-managed settings. Since the effects could vary by the number of advisors, in column (III), we reestimate the specification using $Log\,SubAdvisor$. The results are qualitatively similar.

Taken together, these findings suggest that while co-managed funds do exhibit portfolio characteristics consistent with expanded mandates and greater diversification, these differences do not by themselves attenuate risk-shifting. Under normal circumstances, the costs of coordination across firm boundaries may offset the benefits of collective action. However, when fund performance deteriorates, the benefits from the principal advisor's intervention exceed the cost of coordination, the multiple sub-advisors' propensity to collaborate increases, and the mitigating effect of co-management is realized.

6 Robustness

We perform several robustness checks to support our results further. First, we use an alternative measure of portfolio risk-shifting. Instead of relying on fund returns, we use the fund's portfolio composition to measure risk choices. Second, we conduct a falsification test to assess whether managers are actually tracking fund performance against the designated benchmark. Finally, we examine whether our results are driven by the fund distribution channel—broker-sold versus direct-sold—rather than by outsourcing status.

For brevity, we present these results in section IA.G of the internet appendix. The holdings-based measure yields evidence of risk-shifting similar to that in Table 2; external advisors do not adjust risk in response to deviations from randomly selected benchmarks; and we find no evidence that the distribution channel drives our results. Overall, these findings are consistent with our main results.

7 Conclusion

We investigate the effects of contractual arrangements on the portfolio risk choice of outsourced mutual funds. We first document that the advisors of outsourced mutual funds, who are offered high-powered incentives, engage in mid-year risk-shifting significantly more than advisors of in-house managed funds. Using an instrumental variable approach and matching analysis, we establish a causal relationship between outsourcing and strategic risk-shifting. This behavior can be explained by the implicit optionality in the advisors' payoff structures. We find that concerns regarding retention of the management contract or potential termination drive excessive risk-shifting in outsourced funds. Importantly, performance-based asymmetric contracts of portfolio managers do not determine the risk choices in outsourced funds. Lastly, we examine the mechanisms that mitigate the agency problems and find that contractual arrangements—such as co-location, co-branding, and co-managing—help reduce excessive risk-shifting by outsourced funds and support the efficient expansion of outsourcing as an emerging form of industrial organization.

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Table 1: Summary of the data

This table provides the median of the distribution for the different observed variables in our sample from January 1999 to December 2024. These statistics are provided for the overall sample and by their outsourcing status. The fund is deemed to be outsourced if either the investment advisor or the sub-advisor, if sub-advised, does not belong to the fund complex. The RAR is defined as the ratio of the standard deviation of the fund's excess return in the second half to the standard deviation of the fund's excess return in the first half. Expense ratio and turnover ratio are the annual percentage reported by the fund. Past year return is computed by compounding the previous calendar year return. Semiannual compounded return of the fund in excess of its published benchmark is also reported.

Summary of fund variables			
	In-house funds	**Outsourced funds**	**All funds**
Number of funds			4,010
Number of fund-year observations	30,573	12,216	42,789
Turnover ratio (%)	110.8	61.4	92.1
Expense ratio (%)	1.11	1.12	1.11
Age (in years)	13.4	8.9	11.83
Total net assets (TNA) (millions)	292.6	150.4	239.5
Semi-annual return in excess of benchmark (in %)	-0.357	-0.407	-0.371
Risk adjustment ratio (RAR)	0.968	0.976	0.970
Past year return (%)	10.54	10.58	10.55

Table 2: Outsourcing and risk-shifting

This table shows the interaction between the fund's first-half performance, outsourcing status, and the extent of subsequent risk-shifting. The estimates from a pooled OLS are reported in columns (I) and (II). In columns (III) and (IV), a quantile regression is estimated, where the conditional median function, $Q_{0.5}(.|.)$, is specified as

$$Q_{0.5}(dependent_{j,t}|I_{t,}) = a_t + c_1 * distance_{j,t} + c_2 * exret_{j,t} + \gamma * Controls.$$

The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. All the OLS specifications have time-fixed and fund-fixed effects. For the pooled OLS regressions, standard errors are clustered by fund. For quantile regression, the bootstrapped standard errors are provided in parentheses below the point estimates. The sample used in column (V) covers only outsourced funds, and the sample used in column (VI) covers only in-house managed funds. $I_{performance}$ is an indicator variable which is one if the fund manager's compensation is based on the performance of the fund and zero otherwise. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$Ols: RAR_{i,t}$		$Qtl: RAR_{i,t}$		Outsourced	In-house
	(I)	(II)	(III)	(IV)	(V)	(VI)
Distance	-0.939***	-0.853***	-0.690***	-0.686***	-1.805**	-0.709***
	(0.107)	(0.094)	(0.082)	(0.076)	(0.753)	(0.198)
$Distance*I_{outsourced}$		-0.790**		-0.501**		
		(0.326)		(0.227)		
$Distance*I_{performance}$					0.480	-0.801**
					(1.317)	(0.399)
$I_{outsourced}$	-0.007	-0.004	-0.001	-0.001		
	(0.007)	(0.007)	(0.002)	(0.002)		
$I_{performance}$					0.017	-0.004
					(0.020)	(0.014)
Exret	0.137*	0.138***	0.103***	0.096***	0.129*	0.164***
	(0.026)	(0.026)	(0.019)	(0.021)	(0.067)	(0.042)
Turn ratio	0.001	0.001	0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp ratio	0.473**	0.491**	0.515***	0.512***	0.224	0.807
	(0.211)	(0.186)	(0.053)	(0.182)	(0.168)	(1.355)
Flows	-0.001	-0.001	0.001	0.001	-0.001***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log age	0.007	0.007	0.001	0.001	0.011	0.001
	(0.005)	(0.005)	(0.001)	(0.001)	(0.012)	(0.008)
PastReturn	0.018	0.018	0.012*	0.012	0.091***	-0.036**
	(0.021)	(0.021)	(0.006)	(0.010)	(0.025)	(0.014)
Log size	0.001	0.001	-0.001**	-0.001**	0.004	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
Observations	41,112	41,112	41,112	41,112	8,428	19,022
Adj/Pseudo R^2	0.48	0.48	0.37	0.37	0.52	0.59

Table 3: First Stage of 2SRI

This table shows the results of the first stage of the 2SRI estimation process. Our eventual goal is to showcase the effect of outsourcing on mutual fund risk-shifting. In column (I), we estimate a logit regression where the dependent variable is *Outsourced*, which is an indicator that equals one if the fund management is outsourced and zero otherwise. The observations are at the fund-year level. The variable *LogFamFunds At Inception* is the natural logarithm of the number of funds in the fund family when the fund was created; *LogFamFunds* is the natural logarithm of the number of funds at the beginning of the year; and *LogFamSize* is the natural logarithm of the cumulative AUM of the fund complex; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. Percentile dummies of *Family Size at Inception* (the size of the family that the fund belongs to when the fund was created) are also included in the specification. In addition, dummies for year and fund-family are included in our specification. In column (II), the dependent variable is *Derivative Use*, a binary indicator equal to one if the fund uses any derivatives (options or futures), and zero otherwise. This information is obtained from NSAR filings. In column (III), the dependent variable remains a binary indicator but captures a broader range of investment activities: it equals one if the fund uses derivatives, engages in short selling, buys on margin, or invests in restricted shares. Standard errors are clustered by time and are provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively. McFadden's pseudo R^2 is reported at the bottom of the table.

	(I)	(II)	(III)
	Outsourced	*Derivative Use*	*Broader Constraints*
LogFamFunds At Inception	0.220***	-0.003	0.017
	(0.015)	(0.024)	(0.031)
LogFamFund	0.188***	-0.337***	-0.231***
	(0.070)	(0.068)	(0.061)
LogFamSize	0.007	0.096***	0.002
	(0.015)	(0.030)	(0.026)
Log size	0.013***	0.056***	0.110***
	(0.009)	(0.016)	(0.012)
Log age	-0.078***	0.145***	0.094**
	(0.027)	(0.043)	(0.045)
Exp ratio	2.565***	-13.654***	25.788***
	(0.747)	(4.474)	(4.512)
Turn ratio	0.003***	-0.001***	0.001**
	(0.001)	(0.001)	(0.001)
PastReturn	0.038	-0.126	-0.132
	(0.028)	(0.128)	(0.197)
Flows	-0.019***	-0.020	-0.069
	(0.023)	(0.036)	(0.038)
Observations	32,561	28,498	22,592
Pseudo R^2	0.02	0.07	0.09

Table 4: Second Stage of 2SRI

This table shows the results of the second stage of the 2SRI estimation process. The goal is to showcase the effect of outsourcing on mutual fund risk-shifting. We estimate a pooled regression where the dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The observations are at the fund-year level. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; *Log size* is the log of the fund's TNA at the beginning of the year; *LogFamFunds* is the natural logarithm of the number of funds at the beginning of the year; and *LogFamSize* is the natural logarithm of the cumulative AUM of the fund complex. In addition, we include the residual from the first-stage regression (*FirstStageResiduals*) and its interaction with *Distance*. Percentile dummies of *Family Size at Inception* (the size of the family that the fund belongs to when the fund was created) and a dummy for each year are also included in the specification. The standard errors clustered by fund are provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$Ols : RAR_{i,t}$	$Qtl : RAR_{i,t}$
Distance	-0.786***	-0.662***
	(0.094)	(0.103)
*Distance**$I_{outsourced}$	-1.179**	-0.653**
	(0.502)	(0.319)
$I_{outsourced}$	0.001	0.001
	(0.078)	(0.003)
Exret	0.098***	0.064***
	(0.030)	(0.020)
Turn ratio	0.001	0.001
	(0.001)	(0.001)
Exp ratio	0.300**	0.402
	(0.144)	(0.297)
Flows	-0.001*	-0.001
	(0.001)	(0.001)
Log age	0.007	0.001
	(0.006)	(0.001)
PastReturn	0.023	0.013***
	(0.023)	(0.001)
Log size	-0.001	-0.001
	(0.002)	(0.001)
LogFamFund	-0.009	-0.001
	(0.009)	(0.002)
LogFamSize	0.004	-0.001
	(0.003)	(0.001)
FirstStageResiduals	-0.009	-0.001
	(0.076)	(0.006)
*Distance*FirstStageResiduals*	0.834	0.169
	(0.553)	(1.045)
Observations	32,558	32,558
Adj/Pseudo R^2	0.49	0.35

Table 5: Matched sample: outsourcing and risk-shifting

We report the results from the matched sample study. Funds managed by advisors outside of the fund complex (treated sample) are matched to funds that are managed in-house (control sample) on a variety of dimensions. We match the funds in the treated sample and in the control sample based on size of the fund, age of the fund, expense ratio, turnover ratio, fund flows, and previous year fund return. In addition, we enforce that the treated fund and the matched control fund are in the exact same year and have the same fund style. Figure IA.1 displays the balance of the sample post matching. We run a pooled regression on the matched sample where the dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. In column (I) a Greedy matching algorithm has been used to match the treated and a control sample. In column (II) a similar matching algorithm with replacement is used. Both the specifications have year dummies, and the standard errors are clustered by time. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

$RAR_{i,t}$	Greedy match	Replace match
	(I)	(II)
Distance	-0.765***	-0.816***
	(0.091)	(0.093)
Distance$*I_{outsourced}$	-0.725**	-0.616*
	(0.305)	(0.328)
$I_{outsourced}$	0.001	0.001
	(0.004)	(0.004)
Exret	0.109	0.096
	(0.069)	(0.070)
Turn ratio	0.001	0.001
	(0.001)	(0.001)
Exp ratio	0.313**	0.529***
	(0.143)	(0.154)
Flows	-0.001**	-0.001**
	(0.001)	(0.001)
Log age	-0.001	-0.001
	(0.002)	(0.002)
PastReturn	0.024	0.028
	(0.018)	(0.018)
Log size	-0.004***	-0.004**
	(0.001)	(0.001)
Observations	25,462	26,871
R^2	0.53	0.53

Table 6: Advisor characteristics and risk-shifting

The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. *AdvSize* is the log demeaned total AUM of the advisor(s) managing the fund. $I_{AdvCount}$ is a dummy variable which takes the value of one if the total number of funds (count) under the management of the advisor(s) is greater than the median number and zero otherwise. All the specifications have time-fixed and fund-fixed effects. Standard errors are clustered by fund and provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I)	(II)
$Distance$	-0.850***	-0.767***
	(0.121)	(0.083)
$Distance*I_{outsourced}$	-0.971**	-1.406***
	(0.386)	(0.446)
$Distance*I_{outsourced} * AdvSize$	0.095*	
	(0.053)	
$Distance*I_{outsourced} * I_{AdvCount}$		2.595***
		(0.718)
$I_{outsourced} * AdvSize$	0.001	
	(0.001)	
$I_{outsourced} * I_{AdvCount}$		-0.006
		(0.011)
$Distance*AdvSize$	-0.013	
	(0.027)	
$Distance*I_{AdvCount}$		-2.017***
		(0.391)
$I_{outsourced}$	0.001	0.002
	(0.008)	(0.009)
$Exret$	0.121***	0.126***
	(0.029)	(0.028)
$Turn\ ratio$	0.001	0.001
	(0.001)	(0.001)
$Exp\ ratio$	0.490***	0.488***
	(0.174)	(0.177)
$Flows$	-0.001	-0.001
	(0.001)	(0.001)
$Log\,age$	0.008	0.007
	(0.005)	(0.005)
$PastReturn$	0.019	0.020
	(0.023)	(0.023)
$Log\,size$	0.001	0.001
	(0.001)	(0.001)
$AdvSize$	0.001	
	(0.002)	
$I_{AdvCount}$		0.002
		(0.006)
Observations	32,611	32,611
R^2	0.52	0.52

Table 7: Risk-Shifting and Performance

This table shows the Fama-MacBeth estimates of quarterly fund alphas regressed on fund characteristics lagged by one quarter. The dependent variable in columns (1) and (2) is the fund alpha computed using the Fama-French three-factor return model. In columns (3) and (4), the dependent variable is the fund alpha computed using the Carhart four-factor model. The quarterly alphas are calculated by compounding the monthly alphas, which are estimated using the factor betas computed using a rolling 12-month fund and factor returns. *Turn ratio* is the turnover ratio of the fund at the end of the quarter; *Exp ratio* is the expense ratio of the fund at the end of the quarter; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the previous quarter; *Log age* is the log of the number of years since the first share class in the fund was issued; *Log size* is the log of the fund's TNA at the end of the quarter; and *PastReturn* is the compounded return of the fund for the previous four quarters. $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise. *HighRAR* is an indicator variable, which is one if the fund's quarterly *RAR*, the ratio of the standard deviation of the tracking error from the recent quarter to that from the quarter before, is in the top quintile of the cross-sectional *RAR* distribution. The standard errors are adjusted for serial correlation using Newey-West (1987) lags of order 3 and are shown in parentheses. Time-series averages of quarterly regression R^2s are reported in the last row. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$Alpha_{3-factor}$ (%) (I)	$Alpha_{3-factor}$ (%) (II)	$Alpha_{4-factor}$ (%) (III)	$Alpha_{4-factor}$ (%) (IV)
$I_{outsourced}$	-0.066***	-0.037*	-0.056***	-0.035*
	(0.021)	(0.022)	(0.019)	(0.020)
$HighRAR$*$I_{outsourced}$		-0.152***		-0.114**
		(0.053)		(0.046)
$HighRAR$		0.082		0.047
		(0.066)		(0.051)
$Turn\ ratio$	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$Exp\ ratio$	-0.298***	-0.293***	-0.303***	-0.301***
	(0.059)	(0.059)	(0.065)	(0.066)
$Flows$	0.200	0.185	0.201	0.197
	(0.161)	(0.172)	(0.140)	(0.147)
$Log\,age$	-0.019	-0.018	-0.011	-0.011
	(0.019)	(0.019)	(0.021)	(0.021)
$Log\,size$	-0.005	-0.004	-0.011	-0.010
	(0.012)	(0.012)	(0.011)	(0.011)
$PastReturn$	2.848***	2.864***	2.191***	2.179***
	(0.770)	(0.772)	(0.649)	(0.653)
Observations	154,345	152,419	154,345	152,419
R^2	0.05	0.05	0.04	0.04

Table 8: Risk-Shifting and Co-branding

This table shows the effect of co-branding on risk-shifting among outsourced funds. A co-branding arrangement is one where the name of the sub-advisor is included in the fund name. The fund family partners with a sub-advisor to capitalize on the sub-advisor's reputation. The estimates are from a pooled OLS regression, and the sample includes only the outsourced funds. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable $Exret$ is the fund's first-half return in excess of its own self-designated benchmark; $Distance$ is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{Co-brand}$ is an indicator variable that takes the value of one if the fund is co-branded and zero otherwise; $Exp\ ratio$ is the expense ratio of the fund at the beginning of the year; $Turn\ ratio$ is the turnover ratio of the fund at the beginning of the year; $Flows$ is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; $Log\ age$ is the log of the number of years since the first share class in the fund was issued; $PastReturn$ is the compounded return of the fund for the previous calendar year; and $Log\ size$ is the log of the fund's TNA at the beginning of the year. *Log subadvisor* and *Log Advisor* are the log number of sub-advisors and advisers, repectively, in the fund. All the specifications have time-fixed and fund-fixed effects. Standard errors are clustered by fund and provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$RAR_{i,t}$
$Distance$	-2.875***
	(0.572)
$Distance$*$I_{\{Co-brand\}}$	1.831**
	(0.737)
$I_{\{Co-brand\}}$	-0.012
	(0.013)
$Exret$	0.059
	(0.055)
$Turn\ ratio$	-0.001
	(0.001)
$Exp\ ratio$	0.387***
	(0.117)
$Flows$	-0.001
	(0.001)
$Log\,age$	0.008
	(0.011)
$PastReturn$	0.063*
	(0.033)
$Log\,size$	0.001
	(0.003)
$Log\,SubAdvisor$	-0.004
	(0.011)
Observations	9741
R^2	0.51

Table 9: Risk-Shifting in Co-located Advisors

This table shows the effect of co-location of fund complex and advisors on risk-shifting among outsourced funds. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. *GeoDistance* is the log of the distance in km between the registrant and the advisor. When there are multiple advisors, we use the average distance across them. $I_{\{High-GeoDistance\}}$ is an indicator variable which equals one when the distance between the registrant's address and the advisor's address is above the median distance. $I_{\{In-State\}}$ is an indicator variable which equals one when the registrant's address and the advisor's address are in the same state. $I_{\{StyleCohort\}}$, is an indicator variable which equals one if, for a given outsourced fund, there exists another fund in the same family, in the same year, with the same CRSP style code, but managed internally. All the specifications have time-fixed and fund-fixed effects. Standard errors are clustered by fund and provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$RAR_{i,t}$	$RAR_{i,t}$	$RAR_{i,t}$
	(I)	(II)	(III)
Distance	-1.754***	-3.004***	-2.241***
	(0.431)	(0.468)	(0.468)
$Distance*I_{\{High-GeoDistance\}}$	-1.476**		-1.754**
	(0.633)		(0.687)
$Distance*I_{\{In-State\}}$		1.320*	
		(0.684)	
$Distance*I_{\{High-GeoDistance\}}*I_{\{StyleCohort\}}$			2.274
			(2.292)
$I_{\{In-State\}}$		-0.009	
		(0.011)	
$I_{\{High-GeoDistance\}}$	0.006		0.002
	(0.012)		(0.013)
$I_{\{StyleCohort\}}$			-0.001
			(0.012)
$Distance*I_{\{StyleCohort\}}$			-0.591
			(0.843)
Exret	0.145**	0.142**	0.102
	(0.056)	(0.056)	(0.067)
Turn ratio	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
Exp ratio	0.212**	0.203*	0.254**
	(0.096)	(0.108)	(0.118)
Flows	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Log age	0.013	0.013	0.011
	(0.010)	(0.010)	(0.013)
PastReturn	0.061*	0.062*	0.062*
	(0.034)	(0.033)	(0.037)
Log size	-0.002	-0.001	0.001
	(0.003)	(0.003)	(0.004)
Observations	9,709	9,709	7,278
R^2	0.52	0.52	0.51

Table 10: Risk-Shifting in Co-managed funds

In Panel A, we present the sample means of variables for single- and co-managed funds, along with the tests for differences in means. *NewStocks* refers to the number of new stocks held by the fund that it did not hold at any time in the preceding year; *UniqueStocks* denotes the number of stocks held by the fund that no other fund in its style category holds; *RareStocks* denotes the number of stocks held by the fund that are held by no more than 10% of the funds in its style category. *ICI* (Industry Concentration Index) is described in Kacperczyk et al. (2005). *Coverage*, *Balance*, *Diversification*, and *PortfolioLiquidity* are holding based measures described in Pástor et al. (2020). Panel B presents the estimated effect of co-management on risk-shifting behavior among outsourced funds, based on a pooled OLS regression. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year (Equation (1)). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* represent the amount of new money into the fund during the first half of the year, adjusted for returns; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. $I_{\{advisor>1\}}$ is a dummy variable that takes the value of one when the number of fund advisors is greater than one. *Log SubAdvisor* is the log number of sub-advisors in the fund and $I_{\{Below\}}$ is an indicator variable that takes the value of one if the fund return is below the benchmark and zero otherwise. All the specifications in Panel B have time-fixed and fund-fixed effects. Standard errors are clustered by fund and provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	Panel A		
Variable	**Single Managed**	**Co-Managed**	**Diff**
(I)	(II)	(III)	(IV)
NewStocks	21.39***	55.43***	-34.04***
	(0.269)	(1.155)	(0.793)
UniqueStocks	2.001***	2.31***	-0.314*
	(0.074)	(0.166)	(0.166)
RareStocks	37.44***	96.06***	-58.62***
	(0.391)	(1.54)	(1.10)
ICI (%)	10.94***	9.17***	1.77***
	(0.10)	(0.16)	(0.20)
Coverage (%)	3.33***	8.12***	-4.79***
	(0.03)	(0.11)	(0.07)
Balance	0.41***	0.42***	-0.01**
	(0.002)	(0.003)	(0.004)
Diversification (%)	1.45***	3.30***	-1.85***
	(0.02)	(0.05)	(0.04)
PortfolioLiquidity	0.053***	0.099***	-0.045***
	(0.001)	(0.002)	(0.002)

Panel B			
	$RAR_{i,t}$ (I)	$RAR_{i,t}$ (II)	$RAR_{i,t}$ (III)
$Distance$	-2.240***	-2.750***	-2.145**
	(0.445)	(0.901)	(0.953)
$Distance$*$I_{\{advisor>1\}}$	-1.494	-3.568**	
	(0.946)	(1.437)	
$Distance$*$Log\,SubAdvisor$			-1.998**
			(0.893)
$Distance$*$I_{\{advisor>1\}}$*$I_{\{Below\}}$		3.339**	
		(1.602)	
$Distance$*$Log\,SubAdvisor$*$I_{\{Below\}}$			2.752***
			(1.028)
$Distance$*$I_{\{Below\}}$		1.057	0.234
		(1.482)	(1.401)
$I_{\{advisor>1\}}$	0.017	0.002	
	(0.015)	(0.011)	
$Log\,SubAdvisor$			0.002
			(0.003)
$I_{\{advisor>1\}}$*$I_{\{Below\}}$		0.007	
		(0.017)	
$Log\,SubAdvisor$*$I_{\{Below\}}$			0.003
			(0.003)
$I_{\{Below\}}$		0.002	-0.001
		(0.010)	(0.011)
$Exret$	0.084	0.205	0.204
	(0.055)	(0.163)	(0.154)
$Turn\ ratio$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$Exp\ ratio$	0.280**	0.282*	0.257**
	(0.096)	(0.126)	(0.108)
$Flows$	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
$Log\,age$	0.010	0.010	0.011
	(0.010)	(0.010)	(0.010)
$PastReturn$	0.064**	0.064**	0.062*
	(0.032)	(0.032)	(0.033)
$Log\,size$	0.001	0.001	-0.001
	(0.003)	(0.003)	(0.003)
$Observations$	10,057	10,057	10,057
R^2	0.52	0.52	0.52

Figure 1: Distribution of funds managed

The graph plots the histogram of the average number of funds managed by an advisor of outsourced fund(s) in a given year. The average for any given advisor is the time-series average of the funds such an advisor manages. Bin '1' contains advisors with an average less than or equal to one; Bin '2' contains advisors with an average greater than one but less than or equal to two; Bin '3' contains advisors with an average greater than two but less than or equal to three; Bin '4' contains advisors with an average greater than three but less than or equal to four; Bin '5' contains advisors with an average greater than four but less than or equal to five; Bin '5-10' contains advisors with an average greater than five but less than or equal to ten; and Bin 'Above 10' contains advisors with an average greater than ten.

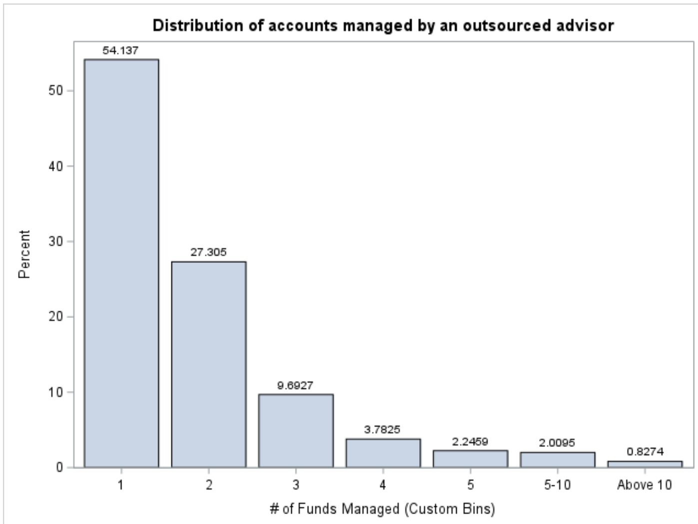
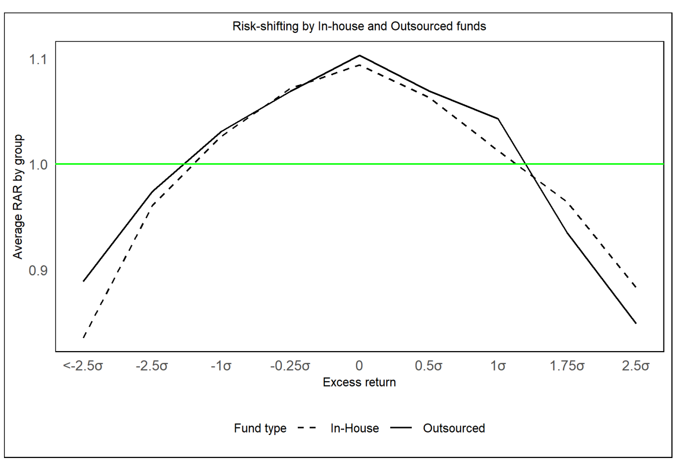


Figure 2: Risk adjustment ratio by management type

The graph below plots the average RAR value for the different partitions of the excess return distribution. The variable RAR is the ratio of the tracking error, as in Equation (1). Excess return is the difference between the fund's return and its self-reported benchmark. Funds are grouped into one of nine bins. Funds are grouped under the $<$-2.5σ category if their mid-year returns are more than 2.5 standard deviations below zero. Funds with mid-year returns between 2.5 standard deviations and 1 standard deviation below zero are grouped under -2.5σ; between 1 standard deviation and 0.25 standard deviations below zero are under -1σ; between 0.25 standard deviations below the benchmark and 0 are under -0.25σ; between 0 and 0.5 standard deviations above the benchmark are under the bin 0; between 0.5 standard deviations and 1 standard deviation are in 0.5σ; between 1 standard deviation and 1.75 standard deviations are in 1σ; between 1.75 standard deviations and 2.5 standard deviations are in 1.75σ; and those above 2.5 standard deviations are in 2.5σ. The average value for each bin, by management type, is plotted.



Internet Appendix to

"The Risk of Outsourcing: How External Advisors Influence Mutual Fund Performance"

IA.A Sub-advisory Contracts

Typically, the hiring and payment of the sub-adviser is handled by the adviser. These arrangements are private contracts, and the specific terms—including compensation formulas—are only disclosed voluntarily. Filings typically describe compensation in broad terms, without specifying whether the fees have a performance component. Below, we provide some examples that help understand this disclosure.

Case 1: The RBB Fund

"*Each Sub-Adviser shall, subject to the supervision and oversight of the Adviser, manage the investment and reinvestment of such portion of the assets of the Subsidiary, as the Adviser may from time to time allocate to such Sub-Adviser for management. The Adviser pays the Sub-Advisers out of its advisory fees.*"

Case 2: Castle focus fund

"*The Sub-Adviser of the Fund has responsibility for providing investment ideas and recommendations for the assets of the Fund, subject to the supervision of the Adviser. As full* *compensation for all services rendered, including investment ideas and recommendations for the assets of the Fund, the Adviser pays the Sub-Adviser a sub-advisor fee.*"

Case 3: Brown Advisory Leaders fund

"*The Adviser pays Brown Advisory Limited a fee out of its advisory fee that is based on a percentage of the average daily net assets managed by Brown Advisory Limited.*"

While disclosure opacity makes systematic data collection infeasible, the evidence that sub-advisers are compensated based on performance is limited: symmetric fulcrum fees are highly unattractive to risk-averse advisors. To provide some suggestive empirical evidence, we collect data from NSAR filings, which require the registrant (the fund) to disclose certain details regarding advisory compensation (not sub-advisors). Assuming these disclosures are informative about sub-advisor arrangements, we find that explicit performance-based fees are uncommon: only 5.8% of advisors in our sample have any part of their compensation tied to fund performance.

IA.B Contract Termination

To shed light on how advisory contracts are actually enforced in practice, we reviewed SEC shareholder filings, focusing on Forms 14A and 14C. These are the filings where funds must disclose material changes to advisory or sub-advisory arrangements. Form 14A (proxy statement) is filed when shareholder approval is required for a new advisory agreement, while Form 14C (information statement) is used when shareholder approval is not required (often under an exemptive "manager-of-managers" order) and funds instead inform shareholders of changes already approved by the board. Since some funds choose to explain the rationale for hiring or firing sub-advisers, they provide rare qualitative insights into the termination decision. In our review, we found that the underperformance was overwhelmingly cited as one of the justifications for sub-adviser termination. For example:

- **Nationwide Mutual Funds**: "*NFA determined to replace Wellington as the Fund's subadviser due to the Fund's underperformance relative to its benchmark and industry peers*"

- **Domini Investment Trust (Impact Equity)**: "*Domini's recommendation was based upon, among other factors, recent changes to the Fund's investment strategy, the Fund's underperformance relative to its benchmark index and peer group of funds, and the quality of the portfolio management team and the depth of firm resources that SSGA FM proposed to provide for the Fund."*

- **Wells Fargo Intrinsic Value Fund**: "*Due to long-term underperformance, the Board decided to terminate the Fund's sub-advisory agreement with Pyramis. LIAC proposed that*

MetWest Capital serve as the Fund's new sub-adviser."

- **BlackRock (Multi-Manager Fund)**: "*The Board considered all factors it believed relevant with respect to its consideration of the Sub-Advisory Agreement, including, among other factors: (a) the history of the Sub-Adviser; (b) the investment performance of the portfolio management of the Sub-Adviser; (c) possible alternatives to the proposed Sub-Advisory Agreement; (d) the fees to be paid pursuant to the Sub-Advisory Agreement; (e) BlackRock's compliance and operational oversight of the Fund and the Sub-Adviser; and (f) other factors deemed relevant by the Trustees.*"

AXA Equitable Funds: "*The Board further considered all factors it deemed relevant with respect to the Portfolio and the New Franklin Mutual Agreement, including: (1) the nature, quality and extent of the overall services provided to the Portfolio by Franklin Mutual; (2) comparative performance information; (3) the level of the sub-advisory fee; (4) economies of scale that may be realized by the Portfolio; and (5) "fall out" benefits that may accrue to Franklin Mutual and its affiliates (i.e., indirect benefits that they would not receive but for their relationship with the Portfolio).*"

IA.C Digital Option

A digital or binary option is a derivative instrument that pays a fixed amount when the underlying asset's value is above the strike price. The payoff is the same regardless of the extent to which the underlying asset's value exceeds the strike price. Using the conventional Black-Scholes model (BS), the price of digital option call option is:

$$D_{call} = e^{-rT}\Phi(d_2), \tag{5}$$

where $\Phi(.)$ is the cumulative probability distribution function of a standard normal variable, and d_2 is the same as the expression in the standard BS model used to price a call or a put option.

$$d_2 = \frac{ln(S/K) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}.$$

The other expression that shows up in the BS model, which we will also use, is:

$$d_1 = \frac{ln(S/K) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}},$$

$$d_2 = d_1 - \sigma\sqrt{T}.$$

Vega of a Digital Option

The vega of a call option (or a put option) measures the sensitivity of the option's price to changes in the volatility of the underlying asset. The partial derivative of the option price with respect to volatility σ:

$$Vega_D = \frac{\partial D}{\partial \sigma} = e^{-rT}\frac{\partial}{\partial \sigma}(\Phi(d_2)).$$

Using the chain rule, we can rewrite it as:

$$Vega_D = e^{-rT}\phi(d_2)\frac{\partial}{\partial \sigma}(d_2),$$

where $\phi(.)$ is the probability density function of a standard normal distribution.

$$\frac{\partial}{\partial \sigma}(d_2) = \frac{\partial}{\partial \sigma}(\frac{ln(S/K) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}})$$

$$\frac{\partial}{\partial \sigma}(d_2) = (-\frac{ln(S/K) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\frac{\sqrt{T}}{\sigma\sqrt{T}} + \frac{\sigma T}{\sigma\sqrt{T}}) = \frac{-1}{\sigma}[d_2 + \sigma\sqrt{T}] = \frac{-d_1}{\sigma}.$$

Therefore, the vega of the digital option is given:

$$Vega_D = e^{-rT}\phi(d_2)\frac{-d_1}{\sigma}. \tag{6}$$

Maximizing the Vega of a Digital Option

To understand the incentive of the investment advisor to risk-shift, we need to identify the region of performance in which the vega is highest.

$$\frac{\partial Vega_D}{\partial S} = -e^{-rT}\left[\frac{\partial \phi(d_2)}{\partial S} \cdot \frac{d_1}{\sigma} + \phi(d_2) \cdot \frac{\partial}{\partial S}\left(\frac{d_1}{\sigma}\right)\right]. \tag{7}$$

Note,

$$\phi(d_2) = \frac{1}{\sqrt{2\pi}} e^{-\frac{d_2^2}{2}},$$

and the following expressions hold:

$$\frac{\partial \phi(d_2)}{\partial d_2} = \phi(d_2) \cdot (-d_2),$$

$$\frac{\partial d_1}{\partial S} = \frac{1}{S\sigma\sqrt{T}},$$

$$\frac{\partial d_2}{\partial S} = \frac{1}{S\sigma\sqrt{T}}.$$

Putting all of this together we get

$$\frac{\partial Vega_D}{\partial S} = -e^{-rT}\left[\left(-\phi(d_2) \cdot \frac{d_2}{S\sigma\sqrt{T}}\right) \cdot \frac{d_1}{\sigma} + \phi(d_2) \cdot \frac{1}{S\sigma^2\sqrt{T}}\right],$$

$$\frac{\partial Vega_D}{\partial S} = -e^{-rT}\phi(d_2) \cdot \frac{1}{S\sigma^2\sqrt{T}}\left(1 - d_2 d_1\right).$$

To maximize $Vega_D$, set $\frac{\partial Vega_D}{\partial S} = 0$:

$$1 - d_2 d_1 = 0.$$

Expressing d_1 in terms of d_2, we have

$$d_2 \cdot \left(d_2 + \sigma\sqrt{T}\right) = 1.$$

Expanding this expression, we get the following quadratic equation:

$$d_2^2 + d_2\sigma\sqrt{T} - 1 = 0.$$

From the definition of d_2, we can solve for S. Overall, the vega of the digital option is maximized when d_2 satisfies:

$$d_2 = \frac{-\sigma\sqrt{T} \pm \sqrt{\left(\sigma\sqrt{T}\right)^2 + 4}}{2}. \tag{8}$$

The corresponding underlying price S is:

$$S = K \cdot e^{d_2 \cdot \sigma\sqrt{T} - \left(r - \frac{\sigma^2}{2}\right)T}. \tag{9}$$

For shorter horizons and reasonable values of the risk-free rate and volatility, one can see that the vega of the option reaches maximum at values of the underlying asset slightly lower than the strike price, i.e., $S \approx K$.

IA.D Impact of Covid-19 pandemic

Table IA.1: Outsourcing and risk-shifting

The estimates from a pooled OLS are reported in columns (I) and (III). In columns (II) and (IV), a quantile regression at the median is estimated. In columns (I) and (II), we exclude observations for 2020 from our sample. To assess the robustness of our results to a broader pandemic window, in columns (III) and (IV), we exclude observations from 2020-2021. The specification is the same as in Table 2 of the main paper. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. For the pooled OLS regressions, standard errors are clustered by fund. For quantile regression, the bootstrapped standard errors are provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	Excludes 2020		Excludes 2020-2021	
	Ols	*Qtl*	*Ols*	*Qtl*
	(I)	(II)	(III)	(IV)
Distance	-0.909***	-0.678***	-0.887***	-0.679***
	(0.111)	(0.136)	(0.106)	(0.118)
$Distance*I_{outsourced}$	-1.027**	-0.663**	-1.032**	-0.672**
	(0.443)	(0.325)	(0.439)	(0.293)
$I_{outsourced}$	-0.002	-0.001	-0.002	-0.001
	(0.007)	(0.003)	(0.008)	(0.003)
Exret	0.134***	0.086***	0.131***	0.088***
	(0.027)	(0.023)	(0.027)	(0.022)
Turn ratio	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Exp ratio	0.506***	0.505**	0.503***	0.504**
	(0.181)	(0.198)	(0.179)	(0.190)
Flows	-0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Log age	0.008*	0.001	0.010*	0.001
	(0.005)	(0.002)	(0.005)	(0.002)
PastReturn	0.015	0.007	0.012	0.003
	(0.021)	(0.011)	(0.023)	(0.011)
Log size	0.001	-0.001**	0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	39,813	39,813	38,575	38,575
Adj/Pseudo R^2	0.48	0.38	0.48	0.38

IA.E Risk-shifting across performance distribution

Table 2 of the paper identifies the average effects of fund performance on risk-shifting behavior. However, such estimates may mask important heterogeneity in managerial responses across the performance distribution. To further explore this, we fit a piecewise linear specification. Specifically, we partition the performance distribution into four segments based on first-half excess returns ($Exret$), using the 10th, 45th, and 65th percentiles as breakpoints. This stratification yields performance regimes corresponding to "$BottomPerf$" ($Exret <$ 10th percentile), "$LowPerf$" (10th–45th percentile), "$MidPerf$" (45th–65th percentile), and "$HighPerf$" (above 65th percentile). The 10th percentile serves to separate severe underperformance, which may trigger an extreme risk-taking response due to career concerns (see Lee et al. (2019)).

We estimate a piecewise linear regression model with knots at the selected breakpoints and interact each spline component with the outsourcing indicator. The results, presented in Table IA.2, yield several insights. Among in-house funds, the marginal effect of prior performance on subsequent risk-shifting exhibits a concave profile, consistent with the attenuated incentives at the tails. In contrast, the interaction coefficients indicate that outsourced managers do not significantly deviate from in-house ones in the lowest decile, and reduce risk in the 10th–45th percentile range. Importantly, they substantially increase risk in the "near-the-money" region, where the convexity of their incentive structure is most salient. Notably, this incremental risk-shifting is statistically significant and economically meaningful. Finally, in the top region, outsourced managers again reduce risk exposure, with the magnitude of the reduction exceeding the level observed for in-house funds. These patterns reinforce the interpretation that outsourced managers respond strategically to their incentive structure.

Table IA.2: Piecewise linear regression

The dependent variable (RAR) is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year. The variable $Exret$ is the fund's first-half return in excess of its own self-designated benchmark; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; $Exp\ ratio$ is the expense ratio of the fund at the beginning of the year; $Turn\ ratio$ is the turnover ratio of the fund at the beginning of the year; $Flows$ represent the amount of new money into the fund during the first half of the year, adjusted for returns; $Log\ age$ is the log of the number of years since the first share class in the fund was issued; $PastReturn$ is compounded return of the fund for the previous calendar year; and $Log\ size$ is the log of the fund's TNA at the beginning of the year. $BottomPerf$, $LowPerf$, $MedPerf$, and $HighPerf$ refer to four piecewise linear spline terms based on fund's $Exret$. These variables are constructed using breakpoints at the 10th, 45th, and 65th percentiles of the $Exret$ distribution, denoted as b_1, b_2, and b_3, respectively. $BottomPerf$, defined as min($Exret$, b_1), captures the slope of $Exret$ for funds in the bottom 10% of performance; $LowPerf$, defined as max(0, min($Exret$-b_1, b_2-b_1)), captures the incremental slope for funds between the 10th and 45th percentiles; $MidPerf$, defined as max(0, min($Exret$-b_2, b_3-b_2)), captures the incremental slope for funds between the 45th and 65th percentiles; and $HighPerf$, defined as max(0, $Exret$-b_3), captures the slope for funds above the 65th percentile. This specification has time-fixed and fund-fixed effects and the standard errors are clustered by fund. The statistical significance at 1%, 5%, and 10% levels are denoted by *, **, and ***, respectively.

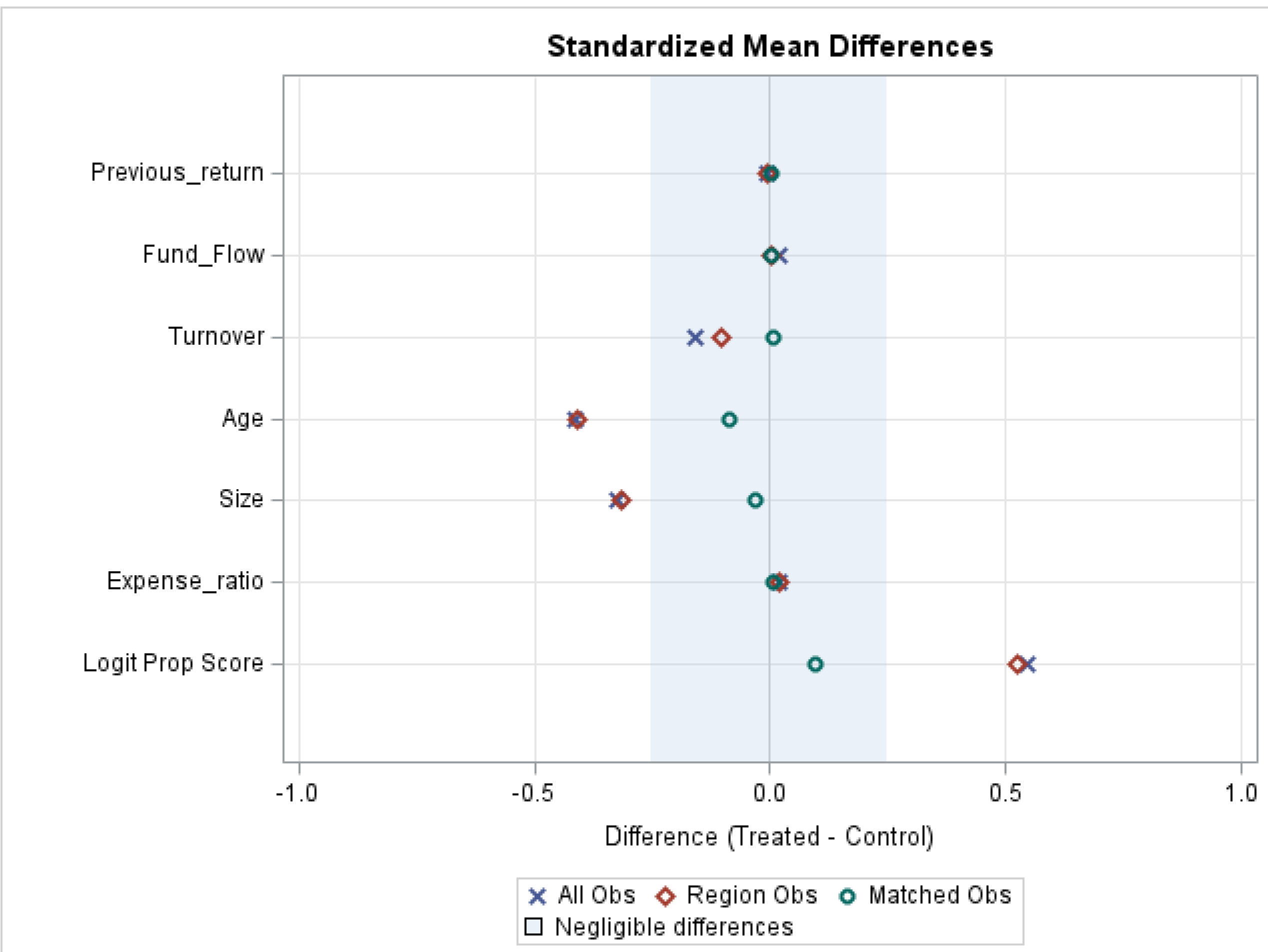
	RAR
$BottomPerf$	0.751***
	(0.094)
$BottomPerf * I_{Outsourced}$	0.262
	(0.184)
$LowPerf$	0.832***
	(0.151)
$LowPerf * I_{Outsourced}$	-0.855***
	(0.299)
$MidPerf$	-0.877***
	(0.334)
$MidPerf * I_{Outsourced}$	1.281**
	(0.650)
$HighPerf$	-0.315***
	(0.055)
$HighPerf * I_{Outsourced}$	-0.110
	(0.112)
$I_{Outsourced}$	0.032*
	(0.018)
$Turn\ ratio$	0.001
	(0.001)
$Exp\ ratio$	0.499**
	(0.201)
$Flows$	-0.001
	(0.001)
$Log\,age$	0.006
	(0.005)
$Log\,size$	0.001
	(0.001)
$PastReturn$	0.018
	(0.020)
Observations	41,112
R^2	0.48

IA.F Balance of the matched observations

Figure IA.1: Covariate balance

In panel A, the graph below plots the covariate balance between the control group and the treated group. The treated group contains funds managed by advisors outside the fund complex and the control group contains funds that are managed in-house. $Expense_Ratio$ is the expense ratio of the fund at the beginning of the year; $Size$ is the log of the fund's TNA at the beginning of the year; Age is the log of the number of years since the first share class in the fund was issued; $Turnover$ is the turnover ratio of the fund at the beginning of the year; $Fund\_Flow$ is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the previous year; and $Previous\_return$ is the return of the fund in the previous calendar year. We match the funds in the treated sample and in the control sample based on size of the fund, age of the fund, expense ratio, turnover ratio, fund flows, and previous year fund return. In addition, we enforce that the treated fund and the matched control fund are in the exact same year and have the same fund style. Panel B shows the data used in the plot. "All" refers to every available observation in the matching process. "Region" refers to observations used for matching that have propensity scores in the common support region. "Matched" refers to the final matched sample.

Panel A: Love Plot



Panel B: Standardized Mean Differences (Treated - Control)						
Variable	Obs	Mean difference	Standard deviation	Standardized difference	Percent reduction	Variance ratio
Logit Prop Score	All	0.303	0.555	0.546		0.814
	Region	0.293		0.528	3.28	0.887
	Matched	0.054		0.097	82.20	1.078
Expense_ratio	All	0.000	0.014	0.020		0.949
	Region	0.000		0.018	6.21	0.946
	Matched	0.000		0.005	71.87	1.173
Size	All	-0.651	2.011	-0.323		0.783
	Region	-0.633		-0.314	2.75	0.796
	Matched	-0.060		-0.029	90.75	0.906
Age	All	-0.365	0.879	-0.415		0.900
	Region	-0.361		-0.410	1.17	0.903
	Matched	-0.074		-0.084	79.67	1.048
Turnover	All	-4.336	27.011	-0.160		0.224
	Region	-2.819		-0.104	34.99	0.676
	Matched	0.137		0.005	96.83	1.644
Fund_flow	All	0.990	52.543	0.018		967.960
	Region	0.989		0.018	0.04	964.488
	Matched	0.047		0.000	95.24	18.317
Previous_return	All	-0.001	0.253	-0.005		1.313
	Region	-0.001		-0.005	8.24	1.311
	Matched	0.000		0.001	77.18	1.330

IA.G Robustness

IA.G.1 Holdings-based risk-shifting

As a robustness check, we follow Kempf et al. (2009) and use portfolio holdings in the Thomson Reuters Mutual Fund Holdings database to construct another measure of the risk-shifting ratio. We first compute the realized portfolio risk in the first half of the year, $\sigma_{j,t}^{(1)}$, using the daily stock returns, the daily benchmark returns for 26 weeks, and the actual portfolio holdings in the first half of the year. This variable is the standard deviation of the difference between the portfolio return and the benchmark return. We then compute the intended portfolio risk for the second period, $\sigma_{j,t}^{(2),int}$, using daily hypothetical portfolio returns based on the actual portfolio weights in the second half of the year and stock returns and benchmark returns from the first half of the year. The standard deviation of this daily time series is $\sigma_{j,t}^{(2),int}$.[10] We finally calculate the intended risk ratio by taking the ratio of intended risk in the second half of the year to the realized risk in the first half of the year:

$$RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}. \tag{10}$$

Using this alternative risk-shifting measure, we re-estimate our baseline results of Table 2. Table IA.3 reports the findings from using the holdings-based measure of risk-shifting. Using this variable does not change the main message from the earlier exercise. We continue to find that funds that have outsourced their management strategically increase their portfolio

[10]Kempf et al. (2009) use weekly returns rather than daily returns. We believe the daily returns provide a better measure of standard deviation and are more consistent with our measure of RAR, which is computed with daily returns.

risk when their performance is around the benchmark.

IA.G.2 Randomization exercise

Given our discussion on the motives of risk-shifting, advisors and managers of outsourced funds have little incentive to respond to the returns of a benchmark that their funds do not track. This suggests that performance benchmarks other than a fund's self-designated benchmark should make no difference to the extent of mid-year risk-shifting. We try a placebo test to examine this implication by randomly assigning a different benchmark to each fund. We repeat the random benchmark assignment 500 times. At each iteration, we run a pooled OLS regression on the randomized sample. All the control variables in Table 2 are used in this analysis. We record the coefficient estimates of the *Distance* and $Distance{*}I_{outsourced}$ variables from each of the 500 iterations. If a manager is indifferent to the benchmark in the portfolio risk decision, we should expect to observe the same relation between *Distance* and *RAR* as in Table 2, after randomizing the benchmark.

Results in Table IA.4 of section IA.G.2 of the internet appendix confirm that the confidence interval of the pooled OLS estimator from the 500 iterations does not contain the original point estimates of -0.853 and -0.790, respectively (see Table 2). In fact, the original point estimates are more than two standard deviations away from the confidence interval. This test demonstrates that external advisors make their risk choices only in response to deviation from the self-designated benchmark and not for randomly selected benchmarks.

IA.G.3 Broker sold funds

Del Guercio and Reuter (2014) argue that mutual fund investors are heterogeneous, and their preferences segment the market for mutual funds. Experienced and knowledgeable investors are likely to self-select into funds sold directly by the fund families to the investors (*direct-sold*). Alternatively, unsophisticated investors seek advice from their investment broker(s) and are more likely to buy funds distributed by such broker(s) (*broker-sold*). The differences in the clientele lead to differences in response from the fund family as well. Del Guercio and Reuter (2014) show that mutual funds sold through brokers face a weaker incentive to generate alpha as the investors in *broker-sold* funds, after a poor performance, do not respond by withdrawing their money as severely as investors in *direct-sold* funds do. Similarly, they argue that, due to their clientele, *direct-sold* funds are less likely to be outsourced when compared to *broker-sold* funds.

Suppose broker-sold funds are more likely to be outsourced and have weaker monitoring, as measured by the investor's flow-performance reaction. In that case, the fund's distribution status may drive our earlier results. We perform a subsample analysis to explore this possibility further. We follow Christoffersen et al. (2013) and use the information in form N-SAR to identify if the fund is *broker-sold.*[11] In our data, approximately 42% of the sample funds are sold via a broker. Panel A of Table IA.5 also shows that, in our sample, only about 30% of the outsourced funds are sold through brokers. This already alleviates some of our concerns.

We also run a pooled OLS regression to consider the fund's distribution status and its

[11] If the amount disclosed in either Q32 or Q33 of form N-SAR is non-zero, the fund is broker-sold. These are the loads received through captive and unaffiliated brokers, respectively. Unfortunately, there is no equivalent question in the N-CEN form. Therefore, this analysis is limited to 2018.

impact on risk-shifting decisions. We introduce a new variable, $I_{broker-sold}$, an indicator variable that is equal to one if the fund is broker-sold and zero otherwise. The results in Panel B of Table IA.5 support our earlier findings. The interaction of $Distance$ and $I_{outsourced}$ continues to have a significant impact on the outsourced fund's risk choices. However, the three-way interaction term is not statistically significant. Overall, the presence of high-powered incentives and the existence of firm boundaries result in increased conditional risk-taking among outsourced funds, which is not influenced much by how the fund is distributed to the investors.

Table IA.3: Outsourcing and Holdings-Based Risk-Shifting

This table shows the interaction between the fund's first-half performance, its outsourcing status, and the extent of the subsequent risk-shifting. The estimates from a pooled OLS and a quantile regression are presented below. The dependent variable is the intended change in portfolio risk computed using holdings of the fund. The intended change in portfolio risk, $RAR^{holdings}_{i,t} = \frac{\sigma^{(2),int}_{i,t}}{\sigma^{(1)}_{i,t}}$, is the ratio of the standard deviation of tracking error of the intended portfolio in the second half of the year to the realized standard deviation of tracking error for the first half of the year. See the text of the paper for more details. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; *PastReturn* is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. All the OLS specifications have time-fixed and fund-fixed effects. For the pooled OLS regressions, standard errors are clustered by fund. For quantile regression, the bootstrapped standard errors are provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$Ols : RAR_{i,t}$		$Qtl : RAR_{i,t}$	
	(I)	(II)	(III)	(IV)
$Distance$	-0.462*	-0.382*	-0.718***	-0.471**
	(0.255)	(0.228)	(0.182)	(0.214)
$Distance*I_{outsourced}$		-1.257***		-0.790**
		(0.380)		(0.373)
$I_{outsourced}$	-0.003	-0.001	-0.001	0.001
	(0.006)	(0.006)	(0.001)	(0.002)
$Exret$	-0.150***	-0.152***	-0.072***	-0.078***
	(0.029)	(0.029)	(0.016)	(0.017)
$Turn\ ratio$	0.001	0.001	-0.001*	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
$Exp\ ratio$	-0.234***	-0.247***	-0.602	-0.589
	(0.088)	(0.082)	(0.379)	(0.363)
$Flows$	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$Log\, age$	0.001	0.001	0.001	0.001
	(0.005)	(0.005)	(0.001)	(0.001)
$PastReturn$	-0.032***	-0.033***	-0.025**	-0.024***
	(0.009)	(0.009)	(0.011)	(0.009)
$Log\, size$	-0.003**	-0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	27,851	27,851	27,851	27,851
Adj/Pseudo R^2	0.08	0.08	0.50	0.50

Table IA.4: Placebo Test

This table summarizes the results from a placebo test via a bootstrapping exercise. The boostrapping exercise randomly assigns a benchmark to each fund. A total of 500 different randomization trials are performed. For each iteration, we perform a pooled OLS regression. These regression specifications are the same as in Column (II) of Table 2. We provide the 5th and 95th percentiles of the point estimates associated with the $Distance$ and $Distance * I_{outsourced}$ variables from the 500 random benchmark assignments exercise. We also provide the coefficient estimates from our baseline regression for comparision.

Confidence Interval from Random Benchmark Assignments Exercise

	5%	95%	Original estimate
$Distance$	-0.393	-0.280	-0.853
$Distance$*$I_{outsourced}$	-0.054	0.187	-0.790

Table IA.5: Outsourcing vs. Broker Sold

The estimates are from a pooled OLS regression. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable $Exret$ is the fund's first-half return in excess of its own self-designated benchmark; $Distance$ is the square of the fund's return in excess of its benchmark, and it measures the extent to which the excess return deviates from zero; $I_{outsourced}$ is an indicator variable which is one if the fund is outsourced and zero otherwise; $I_{broker-sold}$ is an indicator variable which is 1 if the fund is broker-sold and zero otherwise; *Exp ratio* is the expense ratio of the fund at the beginning of the year; $Turn\ ratio$ is the turnover ratio of the fund at the beginning of the year; $Flows$ is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Log age* is the log of the number of years since the first share class in the fund was issued; $PastReturn$ is the compounded return of the fund for the previous calendar year; and *Log size* is the log of the fund's TNA at the beginning of the year. All the specifications have time-fixed and fund-fixed effects. Standard errors are clustered by fund and provided in parentheses below the point estimates. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A: Summary of data

	In-house		Outsourced	
	Direct sold	Broker sold	Direct sold	Broker sold
Number of fund-year observation	7,551	6,632	4,349	1,927
% of sample	36.91	32.42	21.26	9.42

Panel B: Pooled OLS regression

	$RAR_{i,t}$
$Distance$	-1.879***
	(0.521)
$Distance$*$I_{outsourced}$	-2.615**
	(1.125)
$Distance$*$I_{broker-sold}$	0.846
	(0.593)
$Distance$*$I_{broker-sold}$*$I_{outsourced}$	-0.910
	(1.498)
$I_{brokered}$	-0.038
	(0.031)
$I_{outsourced}$	-0.004
	(0.021)
$Exret$	0.283***
	(0.069)
$Turn\ ratio$	-0.003
	(0.003)
$Exp\ ratio$	-2.532
	(2.311)
$Flows$	-0.022***
	(0.005)
$Log\,age$	0.007
	(0.015)
$PastReturn$	0.018
	(0.056)
$Log\,size$	0.003
	(0.005)
Observations	17,012
R^2	0.47

IA.H Portfolio manager compensation contract

Case 1. No performance-based compensation

Registrant Name: John Hancock Capital

Fund Name: Classic Value Fund

Year: 2015

Investment Advisor: John Hancock Advisers

Subadvisor (if any): Pzena Investment Management

Portfolio Manager Compensation

Portfolio managers and other investment professionals at Pzena are compensated through a combination of a fixed base salary (set annually), performance bonus and equity ownership, if appropriate due to superior performance. The time frame that Pzena examines for bonus compensation is annual. Pzena considers both quantitative and qualitative factors when determining performance bonuses; however, performance bonuses are not based on investment performance or assets under management. For investment professionals, Pzena examines such things as effort, efficiency, ability to focus on the correct issues, stock modeling ability, and ability to successfully interact with company management. However, Pzena always looks at the person as a whole and contributions that he/she has made and is likely to make in the future. Pzena avoids a compensation model that is driven by individual security performance, as this can lead to short-term thinking which is contrary to the firm's value investment philosophy.

Case 2. Performance-based compensation

*Registrant Name:*Managed Account Series

Fund Name: Mid Cap Dividend Fund

Year: 2016

Investment Advisor: BlackRock Advisors, LLC

Subadvisor (if any): N/A

Portfolio Manager Compensation

The principal components of compensation include a base salary, a performance-based discretionary bonus, participation in various benefits programs and one or more of the incentive compensation programs established by BlackRock.

Base Compensation: Generally, portfolio managers receive base compensation based on their position with the firm.

Discretionary Incentive Compensation: Generally, discretionary incentive compensation for Active Equity portfolio managers is based on a formulaic compensation program. BlackRock's formulaic portfolio manager compensation program is based on team revenue and pre-tax investment performance relative to appropriate competitors or benchmarks over 1-, 3- and 5-year performance periods, as applicable. In most cases, these benchmarks are the same as the benchmark or benchmarks against which the performance of the funds or other accounts managed by the portfolio managers are measured. BlackRock's Chief Investment Officers determine the benchmarks or rankings against which the performance of funds and other accounts managed by each portfolio management team is compared and the period of time over which performance is evaluated.

A smaller element of portfolio manager discretionary compensation may include consideration of: financial results, expense control, profit margins, strategic planning and implementation, quality of client service, market share, corporate reputation, capital allocation, compliance and risk control, leadership, technology and innovation. These factors are considered collectively by BlackRock management and the relevant Chief Investment Officers.

Distribution of Discretionary Incentive Compensation: Discretionary incentive compensation is distributed to portfolio managers in a combination of cash and BlackRock, Inc. restricted stock units which vest ratably over a number of years. Typically, the cash portion of the discretionary incentive compensation, when combined with base salary, represents more than 60% of total compensation for the portfolio managers.