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

ABSTRACT

In a growing trend, mutual fund families are outsourcing the task of portfolio management 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 twice as risky as in-house funds, which leads to their underperformance. However, fund families can curb the excessive risk-shifting by (i) hiring multiple external advisors simultaneously (co-management), (ii) hiring geographically proximate external advisors (co-location), and (iii) invoking the reputation of the external advisor(s) while marketing the fund (co-branding).

1 Introduction

Outsourcing of investment advisory functions is growing across the delegated portfolio management industry. As of 2018, over 30 percent of equity mutual funds delegate their investment management process to an external unaffiliated investment 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, Hong, Jiang, and Kubik (2013), in their seminal paper, find that outsourced funds underperform in-house managed funds by about 52 basis points a year. Chuprinin, Massa, and Schumacher (2015), Moreno, Rodriguez, and Zambrana (2018) and Broman, Densmore, and Shum Nolan (2023) also confirm this finding in different samples that use both domestic and international mutual funds.

In this paper, we investigate the source of underperformance among outsourced funds and argue that it stems from the agency frictions in contracting among two primary agents: the fund family and the external investment advisor. The resulting equilibrium contract incentivizes external advisors to engage in strategic mid-year risk-shifting, which is inefficient from the investor's perspective. The aforementioned agency problems stem from the firm boundaries between the fund family and the external advisor. In the presence of firm boundaries, the fund family cannot coordinate with the external advisor and control some of the key determinants of success in fund management, such as the assignment of manager(s), the compensation structure used, and the monitoring mechanism put in place. Chen et al. (2013) argue that offering the external advisor a contract with high-powered incentives can be optimal in this imperfect informational environment. They empirically validate this intuition and show that the likelihood of fund closure due to poor performance is higher when the fund is outsourced, which is confirmed in our sample as well.

However, in certain states of the world, we believe that these high-powered compensation contracts offered to external advisors have negative externalities as they make the managerial payoff option-like. As outsourced advisors underperform the benchmark, the likelihood of losing their advisory contract in the following period increases, making their payoff zero. The problem is particularly severe when we consider the median advisor in our sample has only *one* fund in their advisory portfolio. Alternatively, outperformance increases the likelihood that their advisory contract will be retained and they will get a large positive payoff. The trade-off between earning a fixed percentage of assets under management (AUM) and being fired is quite steep.[1] While the high variance contract, as implied by the perform-or-perish style of arrangement, is supposed to temper the average risk levels, we believe that certain outsourced funds facing these large trade-offs have an incentive to strategically increase their portfolio risk in the second part of the year, conditional on their mid-year performance. More specifically, when we consider the mid-year performance distribution of outsourced funds, those with performance close to the benchmark return are incentivized to increase their portfolio risk and beat the benchmark, as the payoffs are asymmetric (see Lee, Trzcinka, and Venkatesan (2019)). In other words, the advisors are trying to maximize the vega of the option implicit in their payoff. This risk-shifting incentive is expected to dissipate as fund performance deviates from the benchmark return on either side. We call this the *retention hypothesis* of risk-shifting and argue that this could be an important reason why outsourced funds underperform in-house managed funds (Chen, Hong, Jiang, and Kubik (2013)).

Given that a large percentage of fund families outsource their funds 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. We propose three mechanisms and test their effectiveness. First, 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

[1] Typically, the advisor's contract with the fund complex is specified as a percentage of the fund's AUM and should be symmetric if there is ever a performance bonus (a fulcrum fee). See Elton, Gruber, and Blake (2011) for the details. Only 5 percent of the fund advisors in their sample have a fulcrum component. Besides, this performance bonus is a matter of second-order importance when considering the risk of employment.

promote effective peer-monitoring (see Kandel and Lazear (1992)). Second, geographical proximity matters for effective monitoring (see Kang and Kim (2008) and Jensen, Kim, and Yi (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-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, Rodriguez, and Zambrana (2018)).

To empirically test our hypotheses, we use the universe of U.S. equity mutual funds from 1999 to 2018. 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, Trzcinka, and Venkatesan (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: -1.971) engage in 100% more strategic risk-shifting than in-house (coef: -0.917) 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, Sialm, and Zhang (2011)), the 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. Finally, we rule out the role of the fund's distribution channel, broker-sold or direct-sold, which is often correlated with investor sophistication and the outsourcing choice, in explaining risk-shifting (Del Guercio and Reuter (2014)).

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. This instrument meets the strict exogeneity requirement as the number of funds a family offered at fund inception has nothing to do with mid-year risk-shifting. 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 (10 basis points 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 alternate mechanisms that help align incentives in incomplete contracting environments. More specifically, we test whether the three arrangements, *co-management*, *co-location*, and *co-branding*, have any moderating effect on the intrinsic risk-shifting behavior of the outsourced advisor. In all three instances, we find that mid-year risk-shifting diminishes when the fund complex takes these additional measures to reduce agency frictions. 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, we shed more light on the outsourcing literature (i.e., Chen et al. (2013), Chuprinin, Massa, and Schumacher (2015), Debaere and Evans (2015), and Moreno et al. (2018)) that investigates the various aspects of contract design. In particular, we provide a fresh perspective on the efficiency of existing contracts awarded to advisors of outsourced funds. Prior literature argues that in the presence of externalities from firm boundaries, the high-powered incentives given to these external advisors curb excessive risk-taking.[3] Although the overall fund risk may be diminished, we show that other motives like securing advisory contracts can *implicitly* incentivize advisors to strategically increase portfolio risk around the benchmark and maximize their payoff. Importantly, this affects the average performance of an outsourced mutual fund. Our finding should encourage fund complexes to realize that the contract they provide is not complete and that additional mechanisms are needed to improve investor outcomes. We test the influence of three potential offsetting arrangements, some of which were previously identified by the literature, and show that they mitigate risk-shifting.

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

[3]An example of such an externality is when the outsourced advisors independently manage their own additional fund(s). In this case of side-by-side management, external advisors tend to favor their mutual funds over sub-advised funds in an initial public offering and privileged information allocations and engage in abnormal cross-trading activities (i.e., Chuprinin, Massa, and Schumacher (2015)). This often leads to the underperformance of outsourced funds.

Second, we contribute to the literature on sources of risk-shifting. Broadly speaking, it is known that an implicit incentive (Brown et al. (1996)) driven by a tournament to capture flows or an explicit incentive emanating from asymmetric performance contract (Lee et al. (2019)) leads to risk-shifting. However, this paper highlights the unexplored role of organizational structure and the ensuing contracting equilibrium. In the presence of moral hazard and firm boundaries, the optimal solution of outsourcing is to have a high-powered convex contract, which also leads to conditional risk-shifting.

Third, we contribute to the growing literature that examines the effect of contracting on fund management outcomes. Lee et al. (2019), Ma et al. (2019), Evans et al. (2020), and Evans et al. (2024) are a few articles that showcase the implications of managerial compensation contracts on outcome variables such as return, risk-taking, and within-family dynamics. Our findings present grounds for creating an improved disclosure environment where investors can clearly understand the financial incentives of the outsourced advisor(s) being hired and what measures, if any, the fund family is taking to complete the incomplete contracting environment. For instance, in a co-managed situation, what are the boundaries of responsibility among the advisors and what measures are taken to avoid collusion?

The remainder of this paper proceeds as follows. Section 3 presents the data and reports the sample descriptive statistics. Section 4 provides empirical evidence of increased risk-shifting among outsourced funds. In addition, we establish a causal effect of outsourcing status on risk-shifting decisions. Section 5 presents evidence on how certain features of the industrial organization help overcome the contracting externalities. Section 6 describes the robustness checks. Section 7 provides our concluding remarks.

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, in some cases, a small fraction of the AUM (see Elton et al. (2003)).[4] 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.[5] Unequivocally, 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 65% higher than in-house funds.

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 a small 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 Appendix C, we show that the vega of a digital option (its sensitivity to underlying asset volatility) 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

[4]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."

[5]The Statement of Additional Information discloses the evaluation horizon used by the fund family to determine the portfolio manager's compensation. Portfolio managers are often assessed on 1-, 3-, and 5-year horizons (see Ma et al. (2019) and Lee et al. (2019)). However, when it comes to investment advisory contracts, no formal disclosures are made. Empirically, as Chen et al. (2013) document, the one-year horizon matters a great deal in evaluating fund closure decisions. This is not to preclude the relevance of a longer horizon.

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. Li et al. (2017) and Coles et al. (2006) also provide related evidence regarding the CEO's response to career concerns and vega of the payoff, respectively.

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 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, Trzcinka, and Venkatesan (2019) and Ma, Tang, and Gomez (2019)). Unlike investment advisors, portfolio managers often receive compensation tied asymmetrically to fund performance. In our sample, 72% 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 (*nexus hypothesis*).

However, outsourced fund advisors are typically small, "owner-manager" firms handling a minimal number of accounts.[6] 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.*

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 underperfor-

[6]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)

mance.

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

Our sample of outsourced funds includes many instances where funds are co-managed by multiple external advisors. Kandel and Lazear (1992) document the role of peer influence in such co-managed settings, noting mutual benefits. When several advisors are engaged, peer monitoring is expected to enhance firm productivity and curb excessive risk-taking. The shared basis of compensation among co-managers further reinforces this monitoring effect. Notably, the SEC exempts multi-advised funds from needing shareholder approval to terminate contracts, creating a competitive environment where only high-performing advisors will likely retain their roles. Moreno et al. (2018) argue that multi-advisor structures can help address the lower returns associated with sub-advised portfolios. Additionally, Dass et al. (2013) suggest that the lack of centralized decision-making and the ensuing coordination challenges among multiple sub-advisors may necessitate more advisor intervention, which may naturally limit risk-shifting behavior. Broman et al. (2023) highlight the fund's desire to maintain a sector concentration or a style tilt as some of the instances where supervision from the advisor is needed, as each sub-advisor acts independently without consulting the other sub-advisors.

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

The costs associated with governance and monitoring tend to rise when there is geographic separation between the principal and the agent, as such distance typically reduces oversight of managerial decisions and limits information spillovers through social networks (see Kang and Kim (2008) and Jensen et al. (2015)). Since outsourced advisors operate outside the fund company's internal structure, we anticipate that the physical distance between the fund company and the advisor will significantly impact the effectiveness of monitoring.

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

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

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. Funds' benchmarks became available after the Securities and Exchange Commission (SEC) mandated that each fund's prospectus include the fund's historical returns as well as its passive benchmark. Our sample period begins in January 1999. We cover funds until December 2018. 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.[7] More specifically, we calculate the sum of assets across all share classes and compute the value-weighted average of fund characteristics across share classes. To compute the intended relative risk of each fund, we use holdings data from the Thomson Reuters Mutual Fund Holdings database.

We also 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

[7]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.

our review of the Form ADV shows affiliation, we identify that 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. We follow Chen et al. (2013) and identify the fund as outsourced if at least one investment advisor's name differs from the name of the fund complex, and that advisor does not belong to the same business group as the fund complex. 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 advisor 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 to identify whether they have certain characteristics. More precisely, we record whether an incentive bonus exists, whether the bonus is tied to the fund's investment performance, and whether the benchmark is clearly mentioned. In addition, by reading the SAI, we can identify the compensation structure of sub-advisors if fund management is outsourced. We classify the compensation structure of the sub-advisor(s) similarly.

Our sample contains 3,527 unique funds and 35,338 fund-year observations for which complete data regarding fund returns, fund characteristics, and benchmark returns is available. In Table 1, the average in-house fund is 11.5 years old, while the average outsourced fund is 7.5 years old. An outsourced fund charges a slightly higher expense ratio of 1.2 percent of AUM than a typical fund. Lastly, over the past two decades, outsourced funds have displayed a gradual increase in numbers, and in 2018, approximately 3 out of 10 funds outsource the management of funds to sub-advisors.

To evaluate the importance of each advisory contract, we plot the histogram of the average number of mutual funds each advisor of outsourced funds manages in a year. The average for any given advisor is the time-series average of the funds such an advisor manages in our sample. Panel A in Figure 1 plots the percentage of advisors in the six non-equal bins. Bin '1' contains advisors with an average less than or equal to one fund; Bin '2' contains advisors with an average greater than one but less than or equal to two funds; Bin '3' contains advisors with an average greater than two but less than or equal to three funds; Bin '4' contains advisors with an average greater than three but less than or equal to four funds; Bin '5' contains advisors with an average greater than four but less than or equal to five funds; Bin '5-10' contains advisors with an average greater than five but less than or equal to ten funds; and Bin 'Above 10' contains advisors with an average greater than ten funds. The histogram displays the exact percentage of advisors in the bin(s) for our sample. Clearly, bin '1' includes more than 50% of the sample of advisors, indicating that the median advisor manages no more than one outsourced fund. In panel B, we plot the cumulative distribution of the funds managed by advisors. We also include a vertical line to display the cumulative proportion of advising three or less funds. Our sample shows that 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 compute the excess return 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. For each year, we calculate

$$Exret_{j,t} = (1 + r_{j,t,1}) * (1 + r_{j,t,2}).....(1 + r_{j,t,n}) - (1 + b_{j,t,1}) * (1 + b_{j,t,2}).....(1 + b_{j,t,n}), \quad (2)$$

where $r_{j,t,n}$ is the daily return for fund j in year t, $b_{j,t,n}$ is the daily return on the benchmark associated with fund j, and n is the number of days in the first six months of year t. 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. It is also worth noting that RAR is not the ratio of standard deviations first analyzed by Brown, Harlow, and Starks (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. We graph this relation separately for in-house and outsourced funds. Funds are assigned to one of nine bins. Funds are grouped under the "$< -2.5\sigma$" category if their mid-year excess returns are more than 2.5 standard deviations below zero. Funds with mid-year excess 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 deviation below zero are under "-1σ"; between 0.25 standard deviation below the benchmark and 0 are under "-0.25σ"; between 0 and 0.5 standard deviation above the benchmark are under the bin "0"; between 0.5 standard deviation 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".

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, i.e., in groups "-0.25σ," "0," and "0.5σ." However, in these intervals, the outsourced funds (solid line) increase their portfolio risk much more than the in-house managed funds (dotted line). Below, we will further explore this relation in a multivariate setting.

4.2 Panel regressions

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:

$$\begin{aligned} RAR_{j,t} = a_t + c_1 Distance_{j,t} + c_2 Distance_{j,t} * I_{Outsourced} \\ + c_3 I_{Outsourced} + c_4 Controls_{j,t} + e_{j,t}. \end{aligned} \tag{3}$$

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 (3), $Distance$, 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, Ruenzi, and Thiele (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.

The vast majority of mutual fund managers have variable compensation contracts based on the fund's performance relative to a specified benchmark. Moreover, these contracts are asymmetric: the manager is not penalized if the fund underperforms the benchmark, giving them an incentive to take additional risk. Lee et al. (2019) document that, due to the asymmetric compensation structure, risk-shifting in the second half of the year is inversely related to the distance of the portfolio's return from the benchmark's return. Squaring $Exret$ gives equal importance to returns above and below the benchmark. Based on Lee et al. (2019), 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 1 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.[8] Therefore, we expect the interaction coefficient of $Distance$ and $I_{Outsourced}$, c_2, to have a negative sign.

Column (I) of Table 2 presents the results from a pooled OLS regression. The specification includes the key variable of interest, $Distance$, along with other control variables. The

[8] Table IA.1 in Appendix B provides evidence to support the assumption that the association between fund closure and poor performance is stronger in outsourced funds. We follow Chen et al. (2013) and fit the probit regression specification below:

$$Probability(Closed_{i,t+1} = 1) = \Phi(\mu + \lambda * Control_{i,t}),$$

where $Closed_{i,t+1}$ is a dummy variable that equals one if fund i closed in year $t+1$ and zero otherwise. A fund is defined as closed in a year $t+1$ if it does not have a full set of fund returns in that year and does not appear subsequently in the CRSP database. The function $\Phi(.)$ is the cumulative distribution function of the standard normal variable. We closely follow Chen et al. (2013) and control for similar fund- and family-level characteristics that could also explain the probability of closure. All the specifications also include a time-fixed effect. The standard errors are clustered at the family level and reported in parenthesis below the point estimate. The numbers in the square brackets are the marginal effects of the respective variable. In our sample, the unconditional probability of fund closure in a given year is 3.81%. The marginal effect of $I_{PRET\,LOW,\,t}$, an indicator variable that equals one if the fund's year t benchmark-adjusted performance is below the median and zero otherwise, suggests that a low-performing fund is about 3.076/3.81 = 81% more likely to be closed than other funds. Importantly, the interaction of $I_{Outsourced,\,t}$ and $I_{PRET\,LOW,\,t}$ is positive and statistically significant. We adjust the t-statistics and the average marginal effects to reflect the critique provided in Ai and Norton (2003). The marginal effects imply that an outsourced fund is 1.976/3.076 = 65% more likely to be closed after poor performance than an in-house fund.

standard errors are clustered by time and fund to correct for any correlation in the error terms. 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.

We also estimate a quantile regression model as an alternative to the pooled OLS specification. The robustness of quantile regression to any potential outliers merits its use. In a quantile regression, we estimate the parameters of the conditional quantile function instead of the conditional expectation. We choose to estimate this model at the median of RAR distribution; thus, we examine the response of the median fund managers. As before, all specifications include time-fixed effects. Standard errors, however, are estimated using a bootstrapping process. Columns (III) and (IV) of Table 2 present our results for the quantile regression. Interpreting these point estimates is similar to interpreting OLS estimates; they represent the marginal effect of the independent variable on the dependent variable, holding constant the effect of other independent variables. These estimates, however, are relevant only for the quantile for which they are estimated. 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.

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 2018 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. We label the two groups as "*no performance*" and "*performance*", respectively. $I_{performance}$ is a dummy variable that takes the value of 1 when the manager has a performance-based contract and zero otherwise. In our sample, about 28 percent of the funds do not have their compensation based on fund performance. This number is very similar to the statistic reported in Lee et al. (2019).

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 effects of high-powered incentives on risk-taking, proposed by Chen et al. (2013), are, in effect, offset by the incentives to retain advisory contracts. The implicit optionality in the external advisors' payoffs influences their strategic actions.

4.3 Causal effect of outsourcing

Our results thus far do not claim a causal impact of outsourcing on fund risk-shifting. Furthermore, 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

To examine the causal effect of outsourcing on mutual fund risk-shifting, first, we use an instrumental variable approach. Our analysis 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 ($LogFamFunds_{i,0}$). 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. Importantly, $LogFamFunds_{i,0}$ satisfies the exclusion restriction as it is reasonable to assume that the number of other funds offered at the new fund inception has nothing to do with the manager's current risk choices. In other words, we are assuming that the past number of funds in a family affects risk-shifting only through the outsourcing decision.

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:

$$Pr(Outsourced_{i,t} = 1) = \Gamma(\mu + \phi LogFamFunds_{i,0} + \kappa FamSizeDummies_{i,0}$$
$$+\eta LogFamFunds_{i,t} + \nu LogFamSize_{i,t} + \gamma X_{i,t} + \delta I_t) \quad (4)$$

where $Outsourced_{i,t}$ is a dummy variable that equals 1 if fund i is outsourced in year t and zero otherwise, $LogFamFunds_{i,0}$ is the natural log of 1 plus the number of funds in the family at the inception of the fund, and $LogFamFunds_{i,t}$ is the natural log of 1 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. Our dependent variable takes binary values and so we use the logistic regression to estimate the conditional probability of the fund being outsourced. Γ (.) in Equation (4) represents the logistic distribution function.

The results of the first-stage regression are presented in Table 3. 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.

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:

$$RAR_{i,t} = \mu + \alpha Distance_{i,t} + \beta Distance_{i,t} * I_{Outsourced_{i,t}} + \varphi I_{Outsourced_{i,t}}$$
$$+\kappa FamSizeDummies_{i,0} + \eta LogFamFunds_{i,t} + \theta LogFamSize_{i,t}$$
$$+\gamma X_{i,t} + \delta I_t + \psi FirstStageResiduals_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where $FirstStageResiduals$ is the residuals from the estimation of Equation (4). We fit Equation (5) using a pooled OLS where year dummies are included and the standard errors are clustered by fund. 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 results from our second stage regression. Controlling for the residuals from the first stage, we find a negative and statistically significant coefficient on $Distance$ and, more importantly, on the two-way interaction term between $Distance$ and outsourcing dummy. This result is consistent with our earlier finding. Furthermore, the magnitude of the coefficient has not diminished at all when we instrument for the potential endogenous variable. The insignificant coefficient of $FirstStageResiduals$ and its interaction with $Distance$ suggests that other unexplained factors that affect the outsourcing status of a fund have a limited impact on the fund's risk-taking decisions. Overall, our instrumental variable analysis suggests that the outsourcing of mutual fund management has a causal effect on the risk-shifting decision even after controlling for a potential endogeneity.

4.3.2 Matching analysis

As discussed in the previous section, the management outsourcing decision may take into account the fund, fund family, and manager characteristics. To further claim that fund management outsourcing has a causal effect on the risk-shifting decision, for each fund in the outsourced group (treated sample), we find an observationally similar fund in the non-outsourced group (control sample). More precisely, based on the size, age, expense ratio, turnover ratio, fund flows, and previous year fund return, we match the fund in the treated sample to another fund in the control sample. 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 3 shows the extent of the covariate balances between the two groups. Our matching procedure effectively balances the covariates as the two groups become very similar in the observed dimensions. The overall balance of the propensity scores is also displayed. 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 funds (or the funds that outsource the fund management) in fact shift risk significantly more. Table 5 presents relevant results. In column (I) of the table, we use a greedy matching algorithm to match the treated with the control sample. In column (II), we use an optimal matching algorithm with replacement. As with previous regression results, the coefficient on the interaction term is negative and statistically significant regardless of the matching procedure. As a robustness check, we adopt alternative matching processes, which match on the basis of Mahalanobis distance computed from the covariates rather than the differences in the propensity score of the logit model. The results are qualitatively similar. Overall, this result confirms 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.[9] 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, Wang, and Zheng (2004)). Furthermore, this can lead to a reputation-stretching strategy in terms of future outsourcing arrangements (Chen and Lai (2010) and Moreno et al. (2018)).

We introduce two variables to capture the variation in advisor attributes. First, $AdvSize$ is defined as the log demeaned total AUM of the advisor.[10] Second, we create a dummy variable, $I_{AdvCount}$, which takes the value of 1 when the total number of funds under the management of the advisor is greater than the median number and zero otherwise. Table 6 presents the results from including these two variables in our earlier specification. 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. In the context of international mutual funds, Chuprinin et al. (2015) document that the bargaining power of external advisors increases as their share in the market for outsourcing services increases. Additionally, a higher market share increases the degree of moral hazard and creates opportunities for the external advisor to extract rents (i.e., preferential treatment of their in-house funds at the expense of outsourced funds). This is less of a concern in the case of domestic equity funds

[9] According to the Investment Company Institute, in 2019, the market share of the top 25 fund families is more than 80 percent in the mutual funds industry. For detailed information, visit https://www.ici.org/system/files/2022-05/2022_factbook.pdf. This observation reflects the fact that the marketing and distribution resources of a fund family are an important channel for attracting assets in the retail investor space.

[10] We add the AUM of all the funds the advisor manages in our sample to get the total AUM.

as the market for external investment advisors in the U.S. is is extremely competitive (i.e., Moreno et al. (2018)).

Columns (I) and (II) of Table 6 report the coefficients on the three-way interaction terms $(Distance{*}I_{outsourced}{*}AdvSize)$ and $(Distance{*}I_{outsourced}{*}I_{AdvCount})$. These terms represent the incremental effect on risk-shifting for the advisors with lower employment risk or those with higher reputation concerns. The results clearly indicate that more established advisory firms who manage assets for a host of funds engage in less risk-shifting as these advisors face very little economic loss from a potential termination of an advisory contract. Furthermore, these advisory firms weigh the reputational penalty of being stigmatized as a frequent "risk-shifter" against the long-run gains. Overall, we find substantial support for the *retention hypothesis* of risk-shifting.[11]

4.4 Outsourcing, risk-shifting, and fund performance

Thus far, it is clear that advisors strategically choose to manipulate portfolio risk as it is optimal from their profit maximization perspective. 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

[11] External managers often manage multiple funds from other families and serve other types of institutional investors (i.e., pension funds or university endowments). Chuprinin et al. (2015) and Moreno et al. (2018) focus on the cases where management companies run both in-house and outsourced funds simultaneously to examine the degree of preferential treatment to in-house funds. Our analysis here includes both the side-by-side and the "pure" outsourcing arrangements.

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 (1) and (3) 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 4.5 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 1 if the fund's quarterly RAR, the ratio of the standard deviation of the tracking error from the current quarter to that from the previous quarter, is in the top quintile of the cross-sectional RAR distribution. The variable $HighRAR$ takes the value of zero otherwise. In columns (2) and (4), we interact the $HighRAR$ dummy variable with the outsourcing dummy variable and find that outsourced funds with high RAR are the main reason why outsourced funds underperform on average. When we include this interaction term in the regression specification, we don't find that outsourced funds by themselves underperform. Instead, the outsourced funds that dramatically increase their portfolio risk relative to their cross-sectional peers underperform. 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 15.6 (10.3) basis points per quarter when using the three-factor (four-factor) performance evaluation model.

5 Management Arrangement and Risk-Shifting

So far, our analysis reveals some of the hidden dynamics behind outsourcing arrangements. We document that the underperformance of outsourced funds can be explained by the excessive risk-shifting behavior of the external advisors. In other words, the implicit incentives inherent in the contractual arrangements with an external advisor provide a strong motivation for risk-shifting. The presence of firm boundaries in combination with the implicit optionality in the payoffs oftentimes leads to a suboptimal portfolio choice and poor fund performance. The severity of the distortion in risk choice gets accentuated as well as mitigated in the presence of various contractual features. As a next step, we exploit the variation in the outsourcing environment to test the efficacy of different contractual arrangements in attenuating the principal-agent frictions.

5.1 Co-management by fund advisors

We start by focusing on Hypothesis 3a, which posits that the level of risk-shifting diminishes when multiple advisors manage the fund. This effect might be due to the direct effects of peer monitoring (e.g., Kandel and Lazear (1992)), the legal environment amicable for easy advisor turnover (e.g., Moreno et al. (2018)), or the absence of centralized decision rights (e.g., Dass, Nanda, and Wang (2013)). Regardless, we empirically evaluate if the risk-shifting among outsourced funds is more extreme in those that a single outsourced advisor manages.

To test this hypothesis, we create a dummy variable, $I_{\{advisor>1\}}$, which takes the value of one when there is more than one fund advisor and zero otherwise. Slightly over 29% of the outsourced funds in our sample have more than one external advisor. Table 8 presents the results from including this dummy in the regression. The coefficients on the interaction term ($Distance * I_{\{advisor>1\}}$) represent the incremental effect in co-managed funds. The results clearly indicate that outsourced funds with a single advisor engage in more risk-shifting.

In a related context, Patel and Sarkissian (2017) and Hamilton, Nickerson, and Owan (2003) show that the positive impact of a team is nonlinear in the number of its "members." Therefore, as a next step, we introduce two new dummy variables: $I_{\{1<advisor\leq 5\}}$, and $I_{\{advisor>5\}}$. First, $I_{\{1<advisor\leq 5\}}$ is a dummy variable that takes the value of one when the number of fund advisors is greater than one but less than or equal to five. This represents

about 23% of the outsourced funds sample. Second, $I_{\{advisor>5\}}$ is a dummy variable that takes the value of one when the number of fund advisors is greater than five. About 6% of the outsourced funds have more than five external advisors. We present the regression results of including these variables in column (II) of Table 8. The results lend support to the existence of such nonlinearity. The effects of peer-monitoring do play a role in mitigating risk-shifting when the number of advisors is five or fewer. However, we find that incremental gains are nullified when the number of advisors exceeds five.

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 execute this test, we collect data from the N-SAR filings and the prospectus on the legal address of the fund registrant and that of the advisor. We then compute the geospatial distance ($GeoDistance$) using the latitude and longitude data. 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.

Table 9 presents the results of risk-shifting among outsourced funds using a pooled OLS regression. Consistent with our expectations, we find that geographical proximity also matters. In column (I), the negative coefficient on the two-way interaction term 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 in order to maximize the value of their payoff.[12] 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. Importantly, our key variable, *Distance*, continues to display a negative coefficient with a higher magnitude as this analysis includes a sample of outsourced funds only.

5.3 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 3c, we create a new dummy variable, $I_{\{Co-brand\}}$, that takes the value of one if the fund is co-branded and zero otherwise. For every outsourced fund, we compare the name of the advisor and that of the external advisor with the name of the fund. 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, 34% of the outsourced funds are co-branded.

Table 10 presents the results of risk-shifting among outsourced funds using a pooled OLS regression. The point estimate on *Distance*, -3.759, is more than three times larger than the

[12] Note that we implicitly assume that the portfolio manager(s) of outsourced funds are operating from the registered address of the advisor(s).

corresponding estimate in Table 2 as the current sample includes only the outsourced funds. 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 45% 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.

Obviously, in an outsourcing arrangement, the level of moral hazard and the firm boundaries lead to serious contracting challenges, and no contract can resolve all possible conflicts. However, we find that fund families that use these three mutually non-exclusive mechanisms can abate some of the potential complications of incomplete contracting. In an unreported result, we test for the effects of the presence of at least one of these mitigating mechanisms. About 60% of the outsourced funds use at least one of these contracting tools, and its presence diminishes risk-shifting by over 60%, compared to outsourced funds not having any such mechanism.

6 Robustness

6.1 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, Evans, and Musto (2013) and use the information in form N-SAR to identify if the fund is *broker-sold.*[13] In our data, approximately 42% of the sample funds are sold via a broker. Panel A of Table 11 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 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 11 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.[14] 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.

6.2 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, $\sigma^{(1)}_{j,t}$, using the daily stock returns, the daily benchmark returns for 26 weeks, and the actual

[13] 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.

[14] The interpretation of the interaction of the three variables isn't too difficult in this case as both $I_{brokered}$ and $I_{outsourced}$ are Bernoulli variables.

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 $\sigma_{j,t}^{(2),int}$.[15] 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:

$$RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}. \tag{6}$$

Using this alternative risk-shifting measure, we re-estimate our baseline results of Table 2. Table 12 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 risk when their performance is around the benchmark.

6.3 Placebo test using benchmark randomization

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

[15]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.

$Distance{*}I_{outsourced}$ 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 13 confirm that the confidence interval of the pooled OLS estimator from the 500 iterations does not contain the original point estimates of -0.917 and -1.054, 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.

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. This behavior can be explained by the implicit optionality in the advisors' payoff structures. Using an instrumental variable approach and matching analysis, we establish a causal relationship between outsourcing and strategic risk-shifting. In addition, we find that concerns regarding retention of the management contract or potential termination drive excessive risk-shifting in outsourced funds. Interestingly, performance-based asymmetric contracts do not determine the risk choices in outsourced funds. Lastly, we examine the mechanisms that mitigate the above-discussed agency problems. Contractual arrangements, such as co-managing, co-branding, and co-location, can mitigate excessive risk-shifting by outsourced funds.

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Table 1: Summary of the data

This table provides the summary statistics for our sample of funds from January 1999 to December 2018. Panel A provides the median of the distribution for the different observed variables in our sample. 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. Panel B provides the frequency of funds outsourced in our sample by year.

Panel A: Summary of fund variables

	In-house funds	**Outsourced funds**	**All funds**
Number of funds			3,527
Number of fund-year observations	25,485	9,853	35,338
Turnover ratio (%)	96.1	52.1	80.9
Expense ratio (%)	1.16	1.2	1.17
Age (in years)	11.5	7.5	10.33
Total net assets (TNA) (millions)	247.5	133.7	205.5
Semi-annual return in excess of benchmark (in %)	-0.364	-0.425	-0.382
Risk adjustment ratio (RAR)	0.986	1.0	0.989
Past year return (%)	10.14	10.13	10.14

Panel B: Outsourcing by year			
Year	**Outsourced** (#)	**Total** Funds	**Outsourced** (%)
1999	370	1,612	22.95
2000	399	1,686	23.67
2001	455	1,828	24.89
2002	489	1,914	25.55
2003	476	1,892	25.16
2004	475	1,884	25.21
2005	508	1,858	27.34
2006	518	1,887	27.45
2007	549	1,947	28.20
2008	570	1,931	29.51
2009	509	1,813	28.08
2010	489	1,749	27.96
2011	488	1,717	28.42
2012	477	1,701	28.04
2013	485	1,667	29.09
2014	520	1,707	30.46
2015	531	1,709	31.07
2016	528	1,663	31.75
2017	520	1,598	32.54
2018	497	1,574	31.58
Total	9,853	35,338	27.88

Table 2: Outsourcing and risk-shifting

This table shows the interaction between the fund's first-half performance, oursourcing 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 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	-1.016***	-0.917***	-0.808***	-0.718***	-4.643***	-0.822**
	(0.092)	(0.078)	(0.236)	(0.052)	(0.845)	(0.374)
$Distance*I_{outsourced}$		-1.054**		-0.890***		
		(0.401)		(0.270)		
$Distance*I_{performance}$					0.675	-1.922***
					(1.478)	(0.743)
$I_{outsourced}$	-0.013	-0.009	-0.003	-0.001		
	(0.012)	(0.013)	(0.003)	(0.002)		
$I_{performance}$					0.015	-0.017
					(0.024)	(0.031)
Exret	0.219***	0.223***	0.135***	0.141***	0.393***	0.253***
	(0.075)	(0.076)	(0.027)	(0.021)	(0.103)	(0.084)
Turn ratio	0.001	0.001	0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Exp ratio	0.457	0.490*	0.542***	0.531***	0.533	-1.076
	(0.275)	(0.254)	(0.122)	(0.029)	(3.179)	(2.467)
Flows	-0.001	-0.001	0.001	0.001	-0.001***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log age	0.008	0.008	0.001	0.001	0.026	0.016
	(0.010)	(0.010)	(0.002)	(0.002)	(0.016)	(0.017)
PastReturn	-0.047	-0.047	0.007	0.007	0.103***	-0.102**
	(0.044)	(0.044)	(0.009)	(0.009)	(0.022)	(0.050)
Log size	0.001	0.001	-0.001	-0.001*	0.004	-0.003
	(0.006)	(0.006)	(0.001)	(0.001)	(0.006)	(0.004)
Observations	32,989	32,989	32,989	32,989	5,904	14,385
Adj/Pseudo R^2	0.22	0.22	0.42	0.42	0.54	0.42

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. We estimate a logit regression where the dependent variable is *Outsourced*, which is an indicator that equals 1 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. 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.

	Outsourced
LogFamFunds At Inception	0.303***
	(0.054)
LogFamFund	0.256**
	(0.118)
LogFamSize	-0.028
	(0.043)
Log size	0.124***
	(0.020)
Log age	-0.366***
	(0.058)
Exp ratio	80.42***
	(7.346)
Turn ratio	-0.002
	(0.002)
PastReturn	0.097
	(0.125)
Flows	-0.078***
	(0.027)
Observations	26,685
Pseudo R^2	0.56

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	-0.838***	-0.713***
	(0.110)	(0.158)
$Distance*I_{outsourced}$	-2.016***	-1.353***
	(0.678)	(0.470)
$I_{outsourced}$	0.001	0.002
	(0.108)	(0.004)
Exret	0.198**	0.125***
	(0.083)	(0.028)
Turn ratio	0.001	0.001
	(0.001)	(0.001)
Exp ratio	0.323	0.400**
	(0.326)	(0.163)
Flows	-0.001	-0.001
	(0.001)	(0.001)
Log age	0.012	0.001
	(0.009)	(0.002)
PastReturn	-0.052	0.004
	(0.059)	(0.009)
Log size	-0.001	0.001
	(0.005)	(0.001)
LogFamFund	-0.028	-0.001
	(0.018)	(0.003)
LogFamSize	0.001	-0.002
	(0.006)	(0.001)
FirstStageResiduals	-0.015	-0.004
	(0.104)	(0.007)
*Distance*FirstStageResiduals*	1.336*	0.859
	(0.812)	(1.126)
Observations	26,685	26,685
Adj/Pseudo R^2	0.21	0.37

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 3 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 without 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	-0.881***	-0.825***
	(0.196)	(0.230)
Distance$*I_{outsourced}$	-0.758**	-0.782**
	(0.345)	(0.365)
$I_{outsourced}$	-0.010	-0.013
	(0.011)	(0.012)
Exret	0.074	0.062
	(0.078)	(0.088)
Turn ratio	0.001	0.001
	(0.001)	(0.001)
Exp ratio	0.145	0.104
	(0.348)	(0.355)
Flows	0.001**	0.001**
	(0.001)	(0.001)
Log age	-0.001	0.001
	(0.005)	(0.005)
PastReturn	0.019	0.017
	(0.023)	(0.024)
Log size	-0.004*	-0.004
	(0.002)	(0.002)
Observations	16,034	14,770
R^2	0.28	0.27

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)
$Distance$	-1.547***	-0.889***
	(0.302)	(0.116)
$Distance*I_{outsourced}$	-1.125**	-2.406***
	(0.508)	(0.463)
$Distance*I_{outsourced}*AdvSize$	0.224**	
	(0.099)	
$Distance*I_{outsourced}*I_{AdvCount}$		3.327***
		(0.835)
$I_{outsourced}*AdvSize$	0.002	
	(0.005)	
$I_{outsourced}*I_{AdvCount}$		0.001
		(0.023)
$Distance*AdvSize$	-0.159***	
	(0.056)	
$Distance*I_{AdvCount}$		-2.239***
		(0.629)
$I_{outsourced}$	-0.002	-0.005
	(0.011)	(0.019)
$Exret$	0.102**	0.123***
	(0.047)	(0.044)
$Turn\ ratio$	-0.005	-0.005
	(0.005)	(0.005)
$Exp\ ratio$	0.454**	0.545***
	(0.200)	(0.191)
$Flows$	-0.011*	-0.010*
	(0.006)	(0.006)
$Log\,age$	0.018**	0.018*
	(0.009)	(0.010)
$PastReturn$	-0.033	-0.034
	(0.059)	(0.059)
$Log\,size$	0.002	0.001
	(0.009)	(0.009)
$AdvSize$	-0.005	
	(0.005)	
$I_{AdvCount}$		0.005
		(0.021)
Observations	24,456	24,456
R^2	0.20	0.20

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.

	$Alpha_{3-factor}$ (%) (1)	$Alpha_{3-factor}$ (%) (2)	$Alpha_{4-factor}$ (%) (3)	$Alpha_{4-factor}$ (%) (4)
$I_{outsourced}$	-0.046**	-0.018	-0.0366*	-0.020
	(0.022)	(0.024)	(0.020)	(0.022)
$HighRAR{*}I_{outsourced}$		-0.156***		-0.103**
		(0.057)		(0.047)
HighRAR		0.101		0.047
		(0.084)		(0.059)
Turn ratio	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Exp ratio	-0.327***	-0.325***	-0.299***	-0.300***
	(0.055)	(0.055)	(0.055)	(0.057)
Flows	0.713	0.670	0.575	0.540
	(0.440)	(0.457)	(0.406)	(0.403)
Log age	-0.027	-0.024	-0.028	-0.024
	(0.023)	(0.023)	(0.021)	(0.026)
Log size	0.001	-0.001	-0.008	-0.008
	(0.015)	(0.015)	(0.011)	(0.012)
PastReturn	3.192***	3.197***	2.172***	2.165***
	(0.945)	(0.945)	(0.726)	(0.730)
Observations	124,236	122,360	124,236	122,360
R^2	0.136	0.143	0.102	0.105

Table 8: Risk-Shifting in Co-managed funds

This table shows the effect of having multiple advisors on risk-shifting among outsourced funds. The estimates from a pooled OLS are reported in columns (I) and (II). 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 1 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), $I_{\{advisor>1\}}$ is a dummy variable that takes the value of one when the number of fund advisors is greater than one. The base case, the coefficient for which has not been estimated to avoid multi-colinearity, is when the number of fund advisors is exactly 1. In column (II) we use the same base case. However, $I_{\{1<advisor\leq 5\}}$ is a dummy variable that takes the value of 1 when the number of fund advisors is greater than 1 but less than or equal to 5; and $I_{\{advisor>5\}}$ is a dummy variable that takes the value of 1 when the number of fund advisors is greater than 5. 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.

	$RAR_{i,t}$	$RAR_{i,t}$
	(I)	(II)
Distance	-3.498***	-3.488***
	(0.473)	(0.473)
Distance$*I_{\{advisor>1\}}$	1.458*	
	(0.770)	
Distance$*I_{\{1<advisor\leq 5\}}$		1.814**
		(0.796)
Distance$*I_{\{advisor>5\}}$		-0.840
		(2.012)
$I_{\{advisor>1\}}$	0.001	
	(0.014)	
$I_{\{1<advisor\leq 5\}}$		-0.006
		(0.015)
$I_{\{advisor>5\}}$		0.045
		(0.033)
Exret	0.228***	0.230***
	(0.068)	(0.068)
Turn ratio	-0.002	-0.002
	(0.001)	(0.001)
Exp ratio	0.721***	0.713***
	(0.144)	(0.142)
Flows	-0.012*	-0.012*
	(0.007)	(0.007)
Log age	0.018	0.018
	(0.011)	(0.011)
PastReturn	0.065*	0.065*
	(0.035)	(0.035)
Log size	0.004	0.004
	(0.004)	(0.004)
Observations	8,048	8,048
R^2	0.52	0.52

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 estimates from a pooled OLS are reported in columns (I) and (II). 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. *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 takes the value of 1 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 takes the value of 1 when the registrant's address and the advisor's address are in the same state. 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.

	$RAR_{i,t}$	$RAR_{i,t}$
	(I)	(II)
Distance	-2.458***	-3.628***
	(0.437)	(0.585)
*Distance**$I_{\{High-GeoDistance\}}$	-1.702**	
	(0.726)	
*Distance**$I_{\{In-State\}}$		1.329*
		(0.746)
$I_{\{In-State\}}$		-0.002
		(0.016)
$I_{\{High-GeoDistance\}}$	0.007	
	(0.013)	
Exret	0.245***	0.241***
	(0.070)	(0.070)
Turn ratio	-0.001	-0.001
	(0.004)	(0.004)
Exp ratio	0.479***	0.444***
	(0.128)	(0.135)
Flows	-0.011	-0.011
	(0.009)	(0.008)
Log age	0.020	0.018
	(0.013)	(0.013)
PastReturn	0.067	0.067*
	(0.036)	(0.036)
Log size	0.001	0.002
	(0.005)	(0.005)
Observations	7,718	7,977
R^2	0.52	0.53

Table 10: 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	-3.759***
	(0.467)
$Distance{*}I_{\{Co-brand\}}$	1.710**
	(0.764)
$I_{\{Co-brand\}}$	-0.002
	(0.020)
Exret	0.189***
	(0.070)
Turn ratio	0.001
	(0.003)
Exp ratio	0.763***
	(0.142)
Flows	-0.010
	(0.007)
Log age	0.019
	(0.012)
PastReturn	0.064*
	(0.036)
Log size	0.001
	(0.005)
Log SubAdvisor	0.011
	(0.016)
Log Advisor	-0.147
	(0.090)
Observations	7,169
R^2	0.52

Table 11: 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

Table 12: 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, $RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}$, 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 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	-0.801**	-0.663**	-0.650***	-0.528*
	(0.289)	(0.309)	(0.213)	(0.300)
$Distance{*}I_{outsourced}$		-1.455**		-0.786**
		(0.661)		(0.326)
$I_{outsourced}$	-0.005	-0.002	-0.001	0.001
	(0.005)	(0.004)	(0.002)	(0.002)
Exret	-0.200**	-0.197**	-0.120***	-0.115***
	(0.079)	(0.080)	(0.025)	(0.025)
Turn ratio	0.001	0.001	-0.001**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Exp ratio	-0.620*	-0.632**	-0.491	-0.492
	(0.306)	(0.293)	(0.400)	(0.351)
Flows	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Log age	0.001	0.001	0.002	0.002
	(0.004)	(0.004)	(0.001)	(0.001)
PastReturn	-0.038	-0.038	-0.025**	-0.026**
	(0.032)	(0.032)	(0.012)	(0.012)
Log size	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	21,741	21,741	21,741	21,741
R^2	0.04	0.04	0.06	0.06

Table 13: 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.

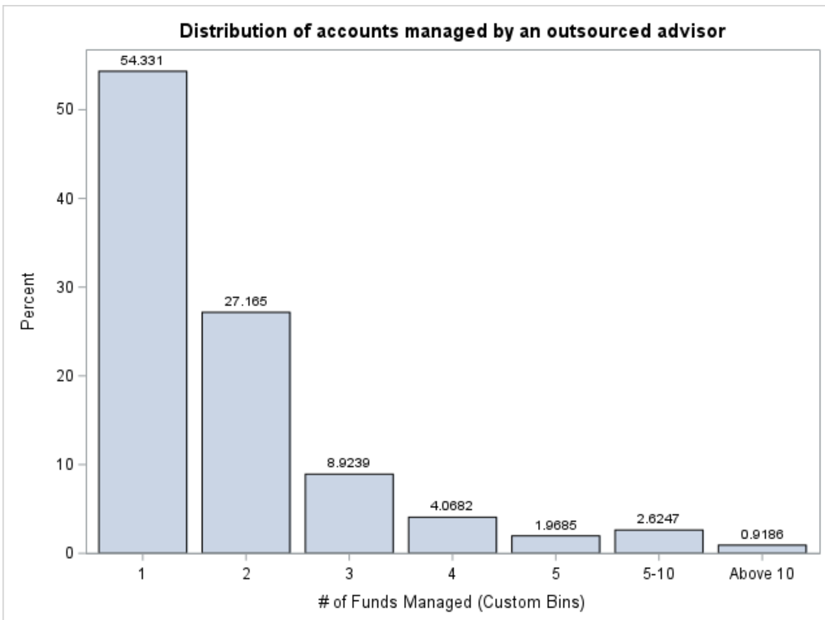
Confidence Interval from Random Benchmark Assignments Exercise

	5%	95%	Original estimate
$Distance$	-0.654	-0.384	-0.917
$Distance^{*}I_{outsourced}$	-0.143	0.234	-1.054

Figure 1: Distribution of funds managed

In panel A below, 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. Panel B plots the cumulative distribution of the same variable (number of funds managed). The vertical line highlights the point where the number of funds managed is three or less.

Panel A: Histogram



Panel B: Cumulative distribution

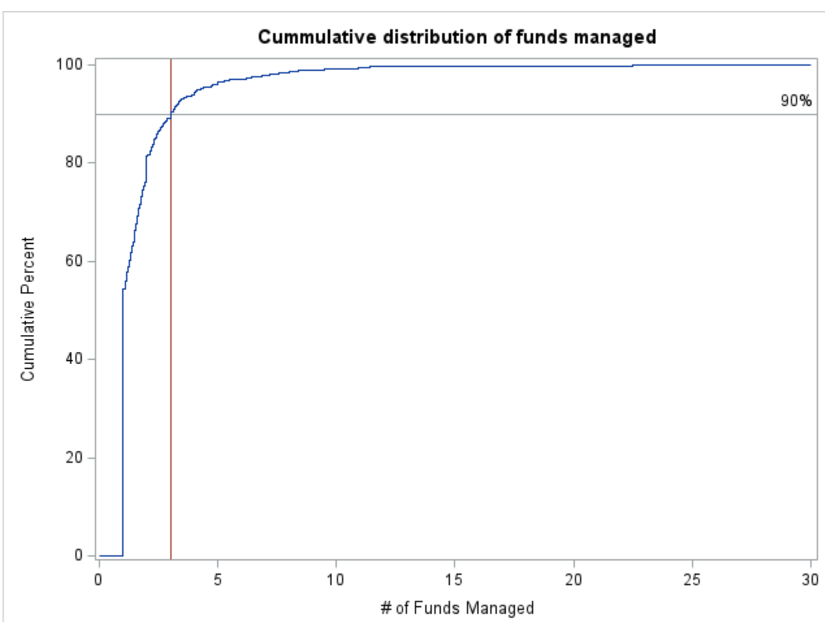


Figure 2: Risk adjustment ratio by management type

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.

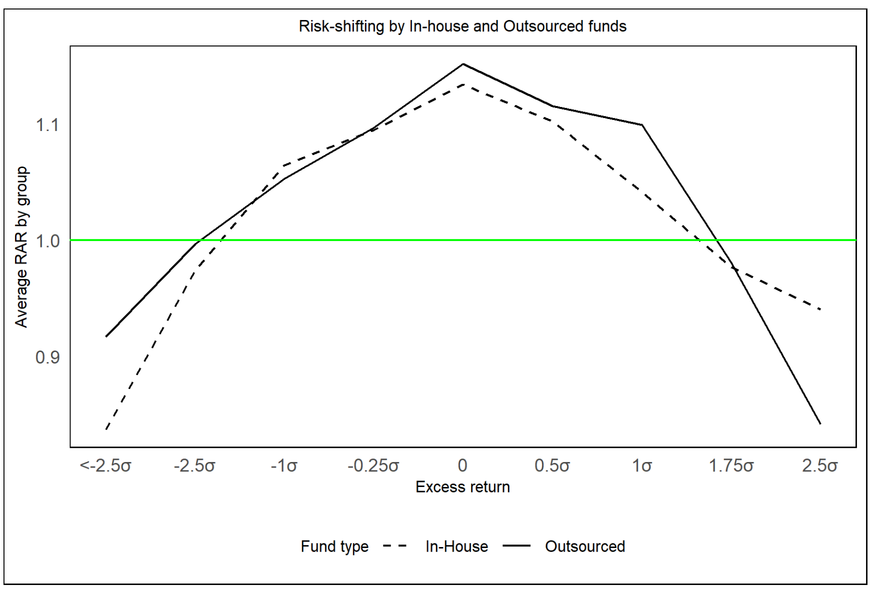
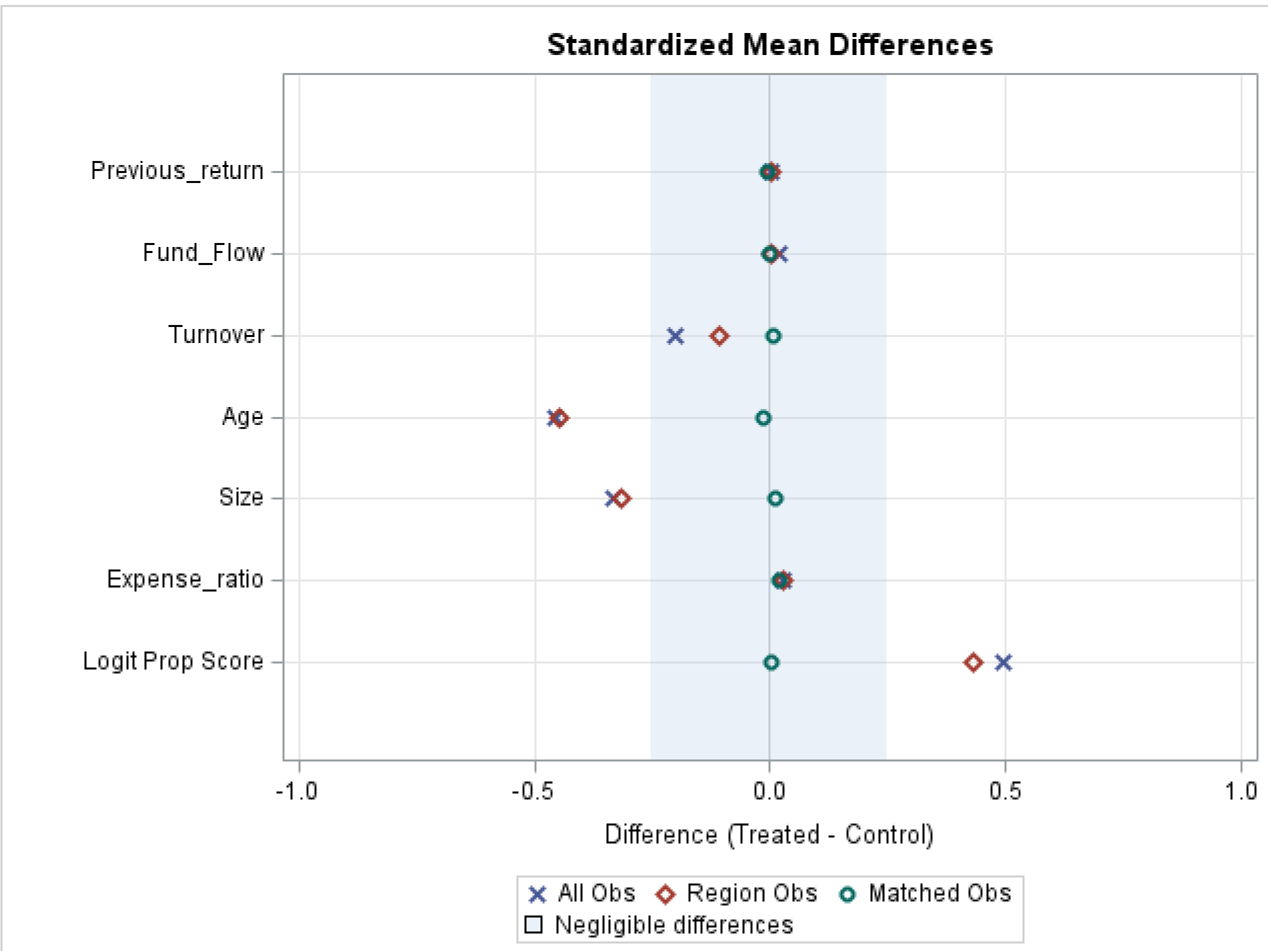


Figure 3: Covariate balance

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	0.341	0.687	0.496		0.549
	Region	0.295		0.430	13.31	0.750
	Matched	0.003		0.004	99.15	1.008
Expense_ratio	All	0.000	0.015	0.029		0.787
	Region	0.000		0.026	10.11	0.782
	Matched	0.000		0.020	30.94	2.709
Size	All	-0.662	1.990	-0.333		0.773
	Region	-0.626		-0.314	5.47	0.799
	Matched	0.023		0.012	96.46	0.891
Age	All	-0.405	0.884	-0.458		0.887
	Region	-0.396		-0.448	2.08	0.892
	Matched	-0.011		-0.013	97.23	1.020
Turnover	All	-5.325	26.401	-0.202		0.062
	Region	-2.835		-0.107	46.76	0.362
	Matched	0.161		0.006	96.98	1.451
Fund_flow	All	1.229	59.113	0.021		86.115
	Region	0.078		0.001	93.67	1.046
	Matched	0.019		0.000	98.46	14.684
Previous_return	All	0.000	0.261	0.001		1.411
	Region	0.000		0.002	0.00	1.407
	Matched	-0.001		-0.004	0.00	1.347

Internet Appendix to

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

A Examples of 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.

B Probability of fund closure

Table IA.1: Estimating the probability of fund closure

We fit a pooled panel probit regression to estimate the determinants of mutual fund closures. The dependent variable $Closed_{t+1}$ is an indicator variable that equals one if the fund is closed in the year $t+1$ and zero otherwise. The observations are at the fund-year level. The explanatory variables are all lagged by a year. The variable $I_{Outsourced}$ is an indicator that equals one if the fund management is outsourced and zero otherwise; $I_{PRET\,LOW}$ is an indicator variable that equals one if the benchmark adjusted fund return in year t is below the median and zero otherwise; *LogFamFunds* is the natural logarithm of the number of funds in the family; and *LogFamSize* is the natural logarithm of the cumulative AUM of the fund complex; *Log size* is the log of the fund's TNA; *Log age* is the log of the number of months since the first share class in the fund was issued; *Exp ratio* is the expense ratio of the fund for the year; *Turn ratio* is the turnover ratio of the fund for the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t}-TNA_{j,t-1}(1+r_{j,t})}{TNA_{j,t-1}}$, during the year. All regressions include year-fixed effects. The standard errors are clustered across the funds within fund families and reported 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. The average marginal effects in percentages (% per year) are shown in the square brackets. The specification in column (3) includes the interaction of two variables, $I_{Outsourced}$, and $I_{PRET\,LOW}$. The average marginal effect of the associated coefficient has been appropriately adjusted (Ai and Norton (2003)). The pseudo-R^2 is reported at the bottom of the table.

		$Closed_{t+1}$	
	(1)	(2)	(3)
$I_{Outsourced,\,t}$	0.161***	0.102***	-0.032
	(0.035)	(0.038)	(0.067)
	[1.579]	[0.892]	[.919]
$I_{PRET\,LOW,\,t}$	0.362***	0.381***	0.322***
	(0.042)	(0.044)	(0.050)
	[3.174]	[3.061]	[3.076]
$I_{Outsourced,\,t}$* $I_{PRET\,LOW,\,t}$			0.196**
			(0.079)
			[1.976]
LogFamFunds		0.102**	0.103**
		(0.041)	(0.041)
		[0.865]	[0.730]
LogFamSize		0.031**	0.031**
		(0.016)	(0.016)
		[0.261]	[0.259]
Log size		-0.200***	-0.201***
		(0.014)	(0.014)
		[-1.695]	[-1.697]
Log age		0.070**	0.070***
		(0.025)	(0.025)
		[0.592]	[0.593]

	$Closed_{t+1}$		
	(I)	(II)	(III)
$Exp\ ratio$		0.604	0.539
		(1.277)	(1.281)
		[5.116]	[4.564]
$Turn\ ratio$		-0.030***	-0.029***
		(0.008)	(0.008)
		[-0.249]	[-0.247]
$Flows$		-0.301***	-0.304***
		(0.043)	(0.043)
		[-2.550]	[-2.577]
Observations	24,181	24,181	24,181
$Pseudo-R^2$	0.06	0.15	0.15

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:

$$D_{call} = e^{-rT}\Phi(d_2), \tag{7}$$

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:

$$Vega_D = e^{-rT}\phi(d_2)\frac{-d_1}{\sigma}. \tag{8}$$

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.

$$\frac{\partial Vega_D}{\partial S} = -e^{-rT}\left[\frac{\partial\phi(d_2)}{\partial S}\cdot\frac{d_1}{\sigma} + \phi(d_2)\cdot\frac{\partial}{\partial S}\left(\frac{d_1}{\sigma}\right)\right]. \tag{9}$$

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:

$$d_2 = \frac{-\sigma\sqrt{T} \pm \sqrt{\left(\sigma\sqrt{T}\right)^2 + 4}}{2}. \tag{10}$$

The corresponding underlying price S is:

$$S = K \cdot e^{d_2 \cdot \sigma \sqrt{T} - \left(r - \frac{\sigma^2}{2}\right) T}. \tag{11}$$

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., $S \approx K$.