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Proximity and Mutual Fund Management Outsourcing:
Evidence from Air Travel Data

BY

Suiheng Guo

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2023

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2023

ACCEPTANCE

This dissertation was prepared under the direction of the *Suiheng Guo* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

Richard Phillips, Dean

DISSERTATION COMMITTEE

Dr. Vikas Agarwal (Chair)

Dr. Lixin Huang

Dr. Baozhong Yang

Dr. Charles Cao (External – Pennsylvania State University)

ABSTRACT

Proximity and Mutual Fund Management Outsourcing:
Evidence from Air Travel Data

BY

Suiheng Guo

8/1/2023

Committee Chair: Vikas Agarwal

Major Academic Unit: Department of Finance

This paper provides novel evidence on the role of proximity in fund management subcontracting. I show that greater geographical proximity facilitates outsourced fund management. Specifically, increased availability of air travel leads to more subcontracting activities, improved performance of subcontracted funds, and lower subadvisory fees. I further show that air travel predicts the decision of fund management to outsource and reduces turnover of subadvisors. Finally, I find that higher air traffic helps subadvisors gain more fund management delegation from fund companies via reductions in information costs. Overall, my findings imply that air travel improves the efficiency of the fund sub-advising market.

**Proximity and Mutual Fund Management Outsourcing:
Evidence from Air Travel Data***

Suiheng Guo[§]

August 2023

This paper provides novel evidence on the role of proximity in fund management subcontracting. I show that greater geographical proximity facilitates outsourced fund management. Specifically, increased availability of air travel leads to more subcontracting activities, improved performance of subcontracted funds, and lower subadvisory fees. I further show that air travel predicts the decision of fund management to outsource and reduces turnover of subadvisors. Finally, I find that higher air traffic helps subadvisors gain more fund management delegation from fund companies via reductions in information costs. Overall, my findings imply that air travel improves the efficiency of the fund sub-advising market.

JEL: D83, G11, G23

Keywords: Fund Management Outsourcing, Geographical Proximity, Air Travel

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1 Introduction

Management sub-advising has gained popularity in the U.S. mutual fund industry in the past two decades. Recent studies show that about 20% of U.S. mutual funds are managed via subcontracting. The market for portfolio management outsourcing was more than \$2.6 trillion in May 2017, accounting for 13.2% of the total assets in the mutual fund industry.¹

Sub-advising benefits fund families primarily due to attracting assets with new investment style offerings. However, there are agency issues in the mutual fund industry (e.g., Huang, Sialm, and Zhang, 2011; Agarwal, Gay, and Ling, 2014; Del Guercio, Genç, and Tran, 2018, etc.), and the nature of external management points to more severe information asymmetry compared to in-house fund management. On the one hand, since the investment skills are private information of asset managers, search costs play an important role in agents' asset delegation decisions (Sirri and Tufano, 1998; Gârleanu and Pedersen, 2018), and thus mutual funds have to bear search costs to select qualified subadvisors. On the other hand, firm boundaries drive the greater challenge for mutual funds to extract information from outside portfolio managers (Chen, Hong, Jiang, and Kubik, 2013) and conduct efficient monitoring. Given the severe information asymmetry issue in the fund sub-advisory market, reductions in the information acquisition costs of mutual funds would influence the decision and the performance of fund management outsourcing. Especially, improved in-person soft information collection by mutual funds will facilitate better performance monitoring and ability learning (such as in-person due diligence), where geographical proximity plays a significant role.

Focusing on management subcontracting in U.S. mutual funds from 2006 to 2017², this paper sheds new light on the role played by proximity in mutual funds' outsourcing decisions and the associated consequences for fund performance. Specifically, this paper mainly aims to show whether greater proximity will lead to more subcontracting activities and (if so) whether improved proximity will result in better performance of sub-advised funds. Answers to these research questions will show the improving effect of proximity on the efficiency of the fund sub-advising market. I measure proximity using air travel data following the literature on travel-induced

¹ See "A Snapshot of the Sub-advisory Market" from Strategic Insight. <https://www.strategic-i.com/blog/snapshot-subadvisory-market/>

² The NSAR filings are rescinded in 2018 and are now replaced by Form N-CEN. I only keep the sample period based on the availability of Form N-SAR for consistency. See section 2.1 for more details.

geographical proximity such as Giroud (2013) and Da, Gurun, Li, and Warachka (2019). The underlying intuition behind this proximity measure is that increased air traffic between an origin city and a destination city reduces travelling time, hence making the two locations more proximate to each other than they would be without such air traffic. In the spirit of Da, Gurun, Li, and Warachka (2019), air traffic is based on the annual number of passengers taking flights between a city with mutual fund headquarters and a city where subadvisor headquarters are located. I also show that using the number of flights between fund-subadvisor city pairs to measure air traffic would also deliver similar empirical results. My findings suggest that increased air traffic induces improvement in both activity and performance of fund management outsourcing.

I first show that air traffic spurs sub-advising at both the extensive margin and intensive margin across fund-subadvisor city pairs. Outsourcing participation is identified at both the fund-subadvisor pair level (fund-level outsourcing events) and the investment company–subadvisor pair level (firm-level outsourcing events). An investment company is a corporation SEC filer identified by a unique Central Index Key (CIK).³ Results from panel regressions show that the outsourcing propensity at the fund level and the number of outsourced funds increase significantly in response to increased air traffic in the following year, and the economic magnitude is also sizable: one log point increase in air traffic for a fund-subadvisor city pair is associated with 6.37% higher likelihood of fund-level outsourcing and 4.31% greater number of outsourcing events compared to an average city pair.⁴ Geographical proximity exerts a stronger influence on the volume of first-time connections since the same level of air traffic shock will lead to an increase in the likelihood and the number of firm-level outsourcing connections of 8.03% and 5.95%, respectively. Given that the demand for fund management outsourcing is higher for large fund companies, who tend to cluster in a few large cities with active air traffic, it is possible that these findings are driven by a limited number of metropolitan cities. I show the robustness of my findings by excluding the top 3, top 5, and top 10 fund cities in my sample.

I find that among the new sub-advising relations, those with greater air traffic are associated with an improvement in fund performance, controlling for fund characteristics, local economic

³ Different from fund companies (fund families), investment companies (CIKs) are distributors of mutual funds (Chen, Hong, Jiang, and Kubik, 2013). One CIK distributes several funds, and one fund family controls several CIKs. For example, the sample of Kwon, Lory, and Qian (2020) contains 91 CIKs, including approximately 1,500 funds. They collect the holdings of a subset of the sample with 59 CIKs under 16 fund families.

⁴ Since the air traffic is a measure based on logarithmic transformation, I use log point as the unit for calculating economic significance, as in other studies on air travel, e.g., Liu and Zheng (2007).

shocks, and fund company–subadvisor city pair fixed effects. Amongst all the newly formed outsourcing relations, those associated with one log point higher air traffic outperform others by 3.90% per year in terms of raw returns. This finding holds when using alternative performance measures. The annual risk-adjusted performance improvement of newly formed sub-advised funds based on excess returns, CAPM, Fama-French three-factor (FF-3) model, and Carhart four-factor (4-Factor) model is 3.80%, 4.80%, 3.60%, and 4.80%, respectively, relative to peer new sub-advising relations. Collectively, these results show that proximity has positive effects on both the decision to outsource and on the performance of sub-advised funds.

Mutual funds may also take advantage of greater proximity to conduct better monitoring of subadvisors, especially when sub-advised funds had inferior performance in the prior year. This hypothesis is supported by empirical evidence. Empirical test results show that poorly performing sub-advised funds are more likely to witness an improvement in future performance with higher air traffic. The Carhart 4-factor risk-adjusted return of past-loser sub-advised funds would increase by as high as 0.12% per year for one log point increase in air traffic between the fund-subadvisor city pair. Further test results show that the return improvements come from sub-advised funds with career concerns, i.e., loser funds with high idiosyncratic risk (Chevalier and Ellison, 1999), and the economic magnitude jumps to 0.34% per year. I also show that improved air traffic significantly reduces the risk-taking behavior of underperforming subadvisors, and I further show that greater idiosyncratic risk taking of subadvisors is detrimental to fund performance. Both empirical findings are consistent with Lee, Patel, and Venkatesan (2022), who document underperforming subadvisors' tendency to conduct strategic risk shifting due to the risk of contract termination. The back-of-the-envelope calculation indicates that the reduced idiosyncratic risk taking due to one log point increase in air traffic accounts for 12% of the performance improvement. These findings suggest that geographical proximity helps mutual funds monitor better to improve subadvisors' performance.

I further examine the dynamics between proximity and advisory fees in the subadvisory market. The test is motivated by the effect of marketing costs in the asset management industry due to the principals' information costs (Sirri and Tufano, 1998; Hortaçsu and Syverson, 2004; Roussanov, Ruan, and Wei, 2021). I hypothesize that increased air traffic enhances the visibility of subadvisors to the local investment companies and hence reduces their marketing efforts. This

is confirmed by the empirical results.⁵ A one-log-point air-traffic shock leads to a decrease in advisory fees charged by a subadvisor by \$3,856.25, accounting for approximately 24% of the estimated average annual marketing costs for financial advisors.⁶ For actively managed equity funds, where information costs are likely to be higher, advisory fees for an average subadvisor are reduced even more, by \$5,663.64.

Using air traffic to identify information costs between mutual funds and subadvisors may suffer from endogeneity issues since passengers' travel decisions are not only influenced by the ease of travel but also influenced by unobservable, time-varying economic trends between the origin-destination city pairs, which are likely to also affect subcontracting events between the city pairs. To deal with this potential endogeneity concern, I use the introduction of new flights as an exogenous shock to air traffic-induced proximity following Giroud (2013) and Ellis, Madureira, and Underwood (2020). I show that the subcontracting activities of active equity funds significantly increase following the introduction of new flights. Finding subadvisors for active equity funds is arguably costly. Therefore, this finding is consistent with the literature that attributes the value of proximity to lowered information costs.

Inspired by Giroud (2013), I also apply Delta Air Lines' 2004 airport hub closing event as an exogenous shock to estimate the causal effect of air traffic on mutual fund subcontracting.⁷ The results show that following Delta's closing of the Dallas–Fort Worth airport hub in 2004, the treated fund-subadvisor city pairs witnessed a significant drop in new mutual fund sub-advising relations in the following three years. These findings provide further empirical evidence that proximity plays an important role in mutual funds' sub-advising decisions.

⁵ The N-SAR B filings only report total advisory fees, which include fund advisors (fund families). Since mutual funds also charge management fees and the day-to-day fund management is subcontracted to subadvisors, I assume that the entire reported advisory fee goes to the subadvisors.

⁶ The sample period for computing the average annual dollar value of advisory firms' marketing costs is 2019 to 2021. The data come from Broadridge's third-annual financial advisor marketing survey, published in 2022. The online survey sample covers 402 financial advisors with over \$10 million in assets under management, including 166 registered investment advisors (RIAs). See <https://www.broadridge.com/assets/pdf/focused-on-growth-2022.pdf> for details.

⁷ The hub-and-spoke transport management system is an outcome of the Airline Deregulation Act of 1978. Major airlines introduced air hubs during the period between the early 1980s to late 1990s (Giroud, 2013), which is earlier than my sample period. So, I could not borrow hub-opening events to conduct robustness tests from Giroud (2013) as Da, Gurun, Li, and Warachka (2019) did. In addition, most of the (limited) hub closing events are due to mergers and acquisitions or reduced demand, either having limited effect on flight changes or suffering from endogeneity concerns. Details of this identification strategy are discussed in Section 4.4.

Besides, I conduct placebo tests to show that changes in proximity other than changes between mutual fund headquarters and subadvisor headquarters (i.e., proximity over branches-to-branches level or branches-to-headquarters level) do not help establish new sub-advising relations. These results also imply that the effect of proximity on management sub-advising stems from reductions in information costs.

Baseline findings show that air traffic helps connect fund companies and subadvisors in the city pairs involved. Therefore, the aggregated departing air traffic from fund-company cities to subadvisor cities (ADAT) should predict fund companies' management outsourcing decisions. This conjecture is supported by empirical results. When ADAT increases by one log point, the odds of a mutual fund assigning a distant subadvisor (whose location is more than 100 miles away from the mutual fund) will increase by 1%, which is equivalent to 23.87% of the unconditional mean. In addition, better information collection by mutual funds may attenuate the existing high-powered incentives imposed on subadvisors stemming from firm boundaries (Chen, Hong, Jiang, and Kubik, 2013) and thus reduce subadvisor turnover. This hypothesis is supported by the data. I conduct empirical analysis similar to Khorana (1996), who studies the determinants of mutual fund manager turnover, and show that subadvisor turnover is less likely to occur as funds encounter higher air traffic availability. A one log point increase in ADAT reduces the unconditional turnover probability by 2.39%.

My last set of tests examine whether air travel would be a characteristic of subadvisor to attract asset delegation businesses from mutual funds. I construct the aggregated arriving air traffic to subadvisor cities from fund-company cities (AAAT) as the key variable to study the ability of a subadvisor to gain business in fund management outsourcing. Models include the interaction item between AAAT and the size of subadvisors' assets under management (subadvisor sizes). The models show a highly significant relation between AAAT and subadvisors' delegated fund management: a one log point increase in AAAT induces a 0.0347 (0.353) log point increase in the number of investment companies (mutual funds) that have asset delegation relations with a subadvisor. Since the unconditional mean of the log number of investment companies (mutual funds) one subadvisor works for is 1.43 (1.62), the economic significance of AAAT on subadvisors' gaining fund-outsourcing business is also substantial. The results are consistent with the value of proximity if we consider subadvisor size as a proxy for reputation: subadvisors whose reputation

is low can benefit more from the reduced information costs due to improved proximity and hence gain more business.

This study contributes to three strands of literature. First, this paper mainly speaks to the literature on the relevance of geographical proximity to the delegated investment management industry. The seminal paper of Coval and Moskowitz (1999) establishes that investors exhibit home bias and use this to their advantage in informed trading. Teo (2009) shows that hedge funds that invest in the Asian capital market exhibit superior performance with a regional presence in Asia, consistent with proximity mitigating informational frictions between hedge funds and their foreign portfolio firms. Sialm, Sun, and Zheng (2020) analyze the implications of fund of hedge funds (FOF) managers' local preference and the consequent outperformance and conclude that proximity allows FOF managers to monitor their investment more closely. This paper applies the extended measurement of proximity beyond distance (in the spirit of Da, Gurun, Li, and Warachka, 2019) and provides complementary evidence on how proximity changes affect the dynamics of the asset management industry through the lens of the fund management sub-advising market.

Second, this study also adds to the nascent literature on the drivers of sub-advising decisions and the performance of sub-advised mutual funds. Kuhnlen (2009) shows that past business connections between fund company directors and advisory firm managers predict hiring relations, and the benefits from improved soft information acquisition and costs from potential collusion due to board-advisor connections offset each other to have no effect on fund performance. Chen, Hong, Jiang, and Kubik (2013) document that the underperformance of sub-advised funds is three times larger than that of funds under in-house management. The authors further attribute the inferior performance of outsourced funds to subadvisors' higher career concerns resulting in less risk taking. Chuprinin, Massa, and Schumacher (2015) document that, in the international mutual fund industry, outsourced funds underperform in-house funds due to subadvisors' preferential treatment. Moreno, Rodriguez, and Zambrana (2018) show that costly contractual arrangements between fund families and advisory firms help to mitigate agency issues in fund management sub-advising and avoid potential underperformance. Arnold, Chambers, Saffi, and Zheng (2021) indicate that fund families change subadvisors in response to past returns, but newly designated subadvisors do not exhibit superior performance, lower risk, and greater flows. This paper provides novel empirical evidence by introducing the proximity factor into the analysis:

outsourced mutual fund management can gain higher efficiency through improved proximity between fund families and subadvisors.

Third, this paper broadly contributes to the large and growing literature on the value of proximity in an underexplored setting of delegated asset management. On the one hand, there is abundant evidence showing that proximity facilitates investment. Giroud (2013) shows a higher level of investment from firm headquarters to destination plants after the introduction of new flights due to less costly monitoring. Agarwal and Hauswald (2010) and Houston, Itzkowitz, and Naranjo (2011) show that lending decisions and outcomes are related to geographical proximity. Da, Gurun, Li, and Warachka (2019) and Ellis, Madureira, and Underwood (2020) provide evidence that air travel-induced proximity influences mutual fund managers' portfolio management. Using detailed data on company visits by Chinese mutual funds, Chen, Qu, Shen, Wang, and Xu (2022) show that mutual fund managers tend to visit local firms, while this preferential company visiting can be significantly reduced on account of improved access to high-speed train travel. Zhang, Kandilov, and Walker (2021) show that cross-border merger and acquisition investments significantly increase after the introduction of new international direct flights. On the other hand, there is growing literature on the relation between proximity and facilitated information acquisition. Through a cross-country study, Bae, Stulz, and Tan (2008) document that local analysts gain information advantage over foreign analysts. Bernstein, Giroud, and Townsend (2016) show that new flights help venture capital firms monitor startups and facilitate the innovation activities of the latter. Kubick, Lockhart, Mills, and Robinson (2017) show that firms closer to the Internal Revenue Service (IRS) avoid more tax due to informational advantages. Huang, Kini, Tyagi, and Wang (2018) document a positive relation between geographical proximity to industry centers and analysts' forecast quality.

The remaining part of this paper is organized as follows: Section II describes the data and variable construction and provides some descriptive information on the sub-advised fund market. Section III presents the main results on how air travel affects the decision and performance of fund management outsourcing. Section IV shows more results on how funds and subadvisors benefit from air travel, respectively. Section V is the conclusion.

2 Data and Measurement

2.1 Data Sources

2.1.1 Data on Fund Management Outsourcing

To get the sample of externally managed mutual funds, I merge US Securities and Exchange Commission (SEC) Form N-SAR and Form ADV filings with the Center for Research in Security Prices (CRSP) database to obtain the fund sub-advising relations, locations of investment companies and subadvisors, advisory fee arrangements, assets under discretionary management of advisory firms, fund size, and fund performance for a sample period spanning from 2006 to 2017. The intersection of all the data sources is described as follows.

In compliance with the disclosure requirements under the Securities Exchange Act of 1934 and the Investment Company Act of 1940, registered investment companies (other than face amount certificate companies) are required to file annual reports for management investment companies (Form N-SAR B filings).⁸ I download all the annual reports from the SEC Electronic Data Gathering Analysis, and Retrieval (EDGAR) database (69,132 files in total) and then parse information about the investment company business, fund advisor relations, and advisory fee. Though some investment management companies voluntarily filed electronic annual reports before 1996, the period for getting consistent filings from EDGAR is from 1996 to 2017. The NSAR filings are rescinded by June 1, 2018, as per the SEC final rule of Investment Company Reporting Modernization, which has required that all registered investment companies (other than face-amount certificate companies) must annually file Form N-CEN to fulfill periodic disclosure requirements since the fiscal year 2018.⁹ Form N-CEN covers similar items of N-SAR filings but discontinues to require mutual funds to report advisory fee structures. Since this research covers studies on the relation between advisory fees and subcontracting relations (see Section 4.2), I only keep the sample period based on the availability of Form N-SAR for consistency.

The study of outsourced mutual funds also relies on SEC Form ADV filings, which have comprehensively covered the identifying and operational information of registered investment advisors (RIA) since 2001. Investment companies' usage of subadvisors is reported in annual

⁸ Face-amount certificate companies are exempt from filing semi-annual/annual reports for management investment companies but are still required to file periodic reports under Section 13 or 15(d) of Securities Exchange Act of 1934.

⁹ Investment companies with a fiscal year-end on April 30 or May 31, 2018 (i.e., for 2017-2018 fiscal year), SEC accepts either Form N-SAR or Form N-CEN. EDGAR still accepts NSAR filings and amendments for previous filings until June 30, 2019 (See: <https://www.sec.gov/investment/investment-company-reporting-modernization-faq>).

reports, but the nature of sub-advising, with external management, means that only unaffiliated subadvisors (i.e., external advisors) are considered “true” subadvisors and only funds managed by unaffiliated subadvisors are considered “sub-advised” mutual funds (i.e., outsourced mutual funds). Since ownership relation determines affiliation, I use the data from Part 1A Schedule A (direct owners of advisors, with acquiring date) and Schedule B (indirect owners of advisors, with acquiring date) of Form ADV to identify the affiliation of reported subadvisors, and the focus of this study is on unaffiliated subadvisors and outsourced mutual funds. In this paper, the word “subadvisor” means unaffiliated subadvisors, and “sub-advised/sub-advising” means (in terms of portfolio management) outsourced/outsourcing. Besides the ownership information, other Form ADV data I use in this paper include the address information of headquarters and other business offices of advisors and total assets under advisors’ discretionary management. I merge NSAR filings and Form ADV data through the shared keyword or SEC file number for RIA (advisor identification).

Since February 2016, the SEC has required investment management companies to apply mandatory series and class (contract) identifiers in their SEC filings. In effect, a series identifier represents funds, and class identifiers represent fund share classes. I merge the SEC series data with CRSP data to obtain information about the performance and summary of the series through CRSP_CIK_MAP, a linking table from the CRSP database that maps SEC investment company Central Index Key (CIK), series identification (ID), and class ID to CRSP fund ID. CRSP fund IDs are share classes of funds, which are under the same investment portfolio, aligned with the portfolio management nature of mutual fund management outsourcing. Therefore, I use series ID as unique identifiers of funds. In another word, delegation relations between investment companies and subadvisors are based on series ID–advisor ID matches.

The research mainly focuses on active equity funds. Active funds are those with missing values for CRSP index fund flags and ETF flags, and equity funds are those whose Lipper assets code is “EQ.”

2.1.2 Air Travel between Investment Management Companies and Advisors

The air travel information is from the T-100 Domestic Segment data. The beginning year of this database is 1990. T-100 Domestic Segment data contains air travel information for all domestic direct flights, such as passengers, number of planned departures, distance between

airports, origin airports, and destination airports. I focus on the flights of passenger aircrafts only (AircraftConfig = 1).

I use the Metro/Micropolitan Statistical Area (MMSA) to match airport locations with the address information of fund companies and advisory firms. Since the address information of investment management companies and advisors contains zip codes, I use US Department of Housing and Urban Development United States Postal Service zip code crosswalk files (mapping zip codes to core-based statistical areas, CBSA) and Census Bureau Delineation Files (mapping CBSA to MMSA) to get MMSAs for these institutions. For T-100 data, where zip codes for airports are not reported, I first merge the T-100 dataset with all airport data from the Airport Data and Information Portal to retrieve zip codes for origin and destination airports. The keyword for the matching is a unique alphanumeric identifier comprising three to four characters assigned to the landing facility, i.e., location identifiers, such as, ORD for Chicago O’Hare. I then add MMSA information to airports, as described before.

2.2 Measurement of Air Travel

In the literature on geographical proximity, air traffic (AT), i.e., the number of airline passengers between two cities each year, is a proxy for air travel (Da, Gurun, Li, and Warachka (2019)). The main variable of interest in this study is also AT. In each calendar year t , the air traffic from MMSA i , where headquarters of mutual fund headquarters are located (fund MMSA), to MMSA j , where headquarters of subadvisors are located (subadvisor MMSA), $AT_{i,j,t}$ is computed as:

$$AT_{i,j,t} = \log (1 + \text{Airline passengers from MMSA } i \text{ to MMSA } j \text{ in } t) \quad (1)$$

It is worth mentioning that fundamentally, it is not the air travel between the fund-subadvisor city pairs that represents the information acquisition costs of mutual funds, but the number of mutual funds visiting subadvisors. However, subadvisor visiting data is not available, and most papers in this strand of literature (e.g., Giroud, 2013; Bernstein, Giroud, and Townsend, 2016; Da, Gurun, Li, and Warachka, 2019; and Ellis, Madureira, and Underwood, 2020, etc.) use the city-pair traffic data as the best feasible proxy of agents’ travelling costs. The only exception is Chen, Qu, Shen, Wang, and Xu (2022), who have company visit data of Chinese mutual funds. Notably, they find that there is a strong association between the city-pair geographical proximity (measured by the bullet train traffic) and mutual funds’ company visits.

Motivated by intuition and the literature (e.g., Bernstein, Giroud, and Townsend, 2016), I assume that if the distance between two MMSAs is shorter than 100 miles, then taking flights would not save travel time and hence set AT as zero. The same filtering also applies when measuring air traffic by the number of departures. AT is a pairwise measurement and is well suited in the tests based on pair-level observations, such as fund-subadvisor city (MMSA) pairs or investment company–subadvisor pairs. Investment companies are fund distributors identified by CIK. However, for tests based on fund-side or subadvisor-side settings, I need to construct derivative measurements based on AT accordingly. For mutual funds, who need to search and monitor subadvisors, access to departing flights seems to be more relevant, and thus for fund-side tests, in each calendar year t , the aggregate departing air traffic for fund MMSA i , $ADAT_{i,t}$ is computed as:

$$ADAT_{i,j,t} = \log(1 + \text{Total Airline passengers departing from MMSA } i \text{ in } t) \quad (2)$$

As for subadvisor companies, in contrast, access to visiting flights seems to be more relevant, and thus for subadvisor-side tests, in each calendar year t , the aggregate arriving air traffic for a subadvisor company MMSA j , $AAAT_{j,t}$ is computed as:

$$AAAT_{i,j,t} = \log(1 + \text{Total Airline passengers arriving in MMSA } j \text{ in } t) \quad (3)$$

3 Summary Statistics

Table 1 displays the big-picture features of the mutual fund subadvisory market from 2006 to 2017. Panel A shows that, on average, 26.59% of mutual funds are under external advisors' management during the sample period, and the fraction of outsourced funds changes little across the years. The numbers reported in Table 1, and the inferred stable trend in fund management outsourcing, are similar to the descriptive statistics in Chen, Hong, Jiang, and Kubik (2013), whose sample period is from 1994 to 2007. Meanwhile, active strategies dominate outsourced funds, as is the case for in-house managed funds. This similarity seems to imply that fund families view management subcontracting as means to expand their coverage of investment strategies rather than as approaches to shrug off passive asset management jobs that are more replaceable and less discretionary. Panel A also exhibits a downtrend in the fund family–level portfolio outsourcing participation, which seems to be at odds with the stable trend in the fraction of the fund-level outsourcing. Noting that there is also an upper trend in the number of total fund families during the sample period, the two seemingly contradicting trends discussed above may reconcile if the

major players in the subadvisory market are more established fund companies. Firstly, since established fund companies have already formed core investment management capabilities, outsourcing may be more aligned with the shared notion that investment ability is the core competitiveness in the asset management industry.¹⁰ Besides, compared to newcomers, established fund companies have better distribution networks and better connections in the business. Therefore, entrenched fund families face higher demand for investment subcontracting and greater capacity to collect information from subadvisors. The difference in fundamentals between fund families with and without subadvisors, which is reported in Panel C, supports the argument that fund families with higher total net assets and longer histories are more likely to hire subadvisors.

[Insert Table 1 Here]

Panel B reports the features of in-house funds and outsourced funds. Except for passive funds, funds managed by external managers are younger and much smaller than funds managed internally. The turnover and distribution (12b-1) fees of funds under subadvisory management are similar to those of in-house funds. These characteristics again echo those reported by Chen, Hong, Jiang, and Kubik (2013). An interesting pattern is that outsourced funds charge higher management fees than internally managed funds, which seems to be driven by rent-collecting of subadvisors: the difference in management fee dwells in actively managed funds, where managerial costs are high, and for funds based on passive strategies, where portfolio management does not require high skills, the management fee gap between in-house funds and outsourced funds almost disappears.

Panel C shows the comparisons of characteristics between fund families that use subadvisors and those that do not. Fund families with higher total net assets and longer histories tend to subcontract portfolio management to external advisory firms. The feature is consistent with the separate equilibrium in conducting costly searches by agencies with different assets to delegate, as modeled by Gârleanu and Pedersen (2018). In addition, fund families with higher market power—reflected by more funds under distribution, higher management fee incomes, and higher 12b-1 fees—are more likely to hire subadvisors. The fundamental features reported in Panel C

¹⁰ According to a 2018 survey conducted by FA Insight based on 264 advisory firms with an annual revenue of more than \$150,000, 74% of the advisory firms (fund families) articulate investment management expertise as the central value-offering area or one of several key value-offering areas for their clients. <https://www.tdainstitutional.com/content/dam/institutional/resources/whitepapers/fa-insight/fa-insight-outsourcing-striking-the-right-balance-bet-customization-and-efficiency-whitepaper.pdf>

suggest that established fund families are the dominating participants in the subadvisory market and thus echo the downward trend in the fraction of fund family–level outsourcing shown in Panel A.

Table 2 reports some summary statistics on the fund management outsourcing market. Panel A reports the management outsourcing and flight connections between Metro/Micropolitan Statistical Areas (MMSAs) of fund companies and subadvisors from 2006 to 2017. The statistics show that the number of fund MMSAs is just above half of the number of subadvisor MMSAs. Being more selective in choosing locations echoes investment companies’ emphasis on product distribution (Chen, Hong, Jiang, and Kubik, 2013), and the dispersion of investment opportunities seems to play a role in the diversified locations of subadvisors. Meanwhile, the more dispersed subadvisor locations also mean that the investment companies need to bear higher information costs to enter management subcontracts. During the sample period, the fraction of fund-subadvisor MMSA pairs (F-S MMSA pairs) with subcontracting connections (subcontracting connection coverage ratio) increases from 7.82% to 9.06%. Table 2 also reports the statistics of the direct-flight coverage of fund-subadvisor MMSA pairs (flight connection coverage ratio). In the spirit of the value of proximity, the flight connections and the flight connection coverage ratios are one-year lagged values. Although there is growth exceeding 30% in the flight connection coverage ratio, it remains lower than 20% at the end of the sample period, indicating the potential relevance in the subadvisory market of the value of proximity induced by air travel improvement. The significantly positive correlation between the subcontracting connection coverage ratio and the flight connection coverage ratio in the preceding year further indicates that the influence of air travel on fund management outsourcing might be substantial. Empirical results from model estimations are provided in the following sections.

[Insert Table 2 Here]

Table 3 reports the summary statistics on air travel data and subcontracting events. The sample period of the air travel statistics is from 2005 to 2016 (one year earlier than the start and end of the sample period). Panel A shows that direct flights of an average fund MMSA can cover 13.26% of all the subadvisor MMSAs, which is close to the average subcontracting connection coverage ratio as discussed in Table 2 (9.10%). This further suggests that investment companies tend to select subadvisors from a pool of third-party advisory firms on their radar. Panel A also exhibits the summary statistics for the annual air travel data at the MMSA-pair level. A significant

variation in air traffic between different F-S MMSA pairs is shown, and the average number of passengers increases with the number of flights at the beginning and then remains almost constant. Panel B shows a high correlation between passengers and flights, comparable to the statistics in Da, Gurun, Li, and Warachka (2019), which is also consistent with the rationale of economies of scale in the airline industry. The following test results show that using departure flights as an alternative proxy for air travel would yield similar findings, further confirming the high correlation between air traffic and departure flights. Panel C reports the statistical features of management outsourcing events across different fund MMSAs and subadvisor MMSAs. The average of firm-level management outsourcing events (i.e., extensive subcontracts only) per year is 0.0249. This number may seem trivial but has significant economic magnitude. If the average number of new subcontracts all come from F-S MMSA pairs that have no prior sub-advising relations, the subcontracting connection coverage ratio will increase by 27.36%. The significant number of new subcontracts and the slow evolution of F-S MMSA subcontracting connections, as shown in Table 2, again suggest the relevance of information costs in the subadvisory market.

[Insert Table 3 Here]

4 Main Results

4.1 Number and Performance of Subcontracts

To show the value of proximity in the setting of fund management outsourcing, I first estimate the panel regression at the level of F-S-MMSA-year as follows:

$$\text{SubcontractingEvents}_{i,j,t} = \beta * \text{AT}_{i,j,t-1} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t} \quad (4)$$

where SubcontractingEvents represents the firm-level or fund-level new subcontracts between fund companies and subadvisors from different F-S MMSA pairs in year t , and new management outsourcing relations are counted both as indicators (taking the value of 1 if there is at least one subcontracting event, and 0 otherwise) and continuous variables; AT is the log of passengers taking flights from the fund-company MMSA i to the subadvisor MMSA j in the last year; θ denotes the fund-MMSA-year fixed effects; δ represents the subadvisor-MMSA-year fixed effects, and μ stands for the F-S MMSA pair fixed effects. If AT facilitates fund management outsourcing through reduction in information costs, then β should be positive and significant.

For the model identified as (4), I regress annual new subcontracts on AT and report the estimates in Table 4. The dependent variable of subcontracting events is measured at the firm level

in Panel A and at the fund level in Panel B. Consistent with proximity mitigating information acquisition costs, increased AT significantly facilitates fund management outsourcing. One log point increase in AT is associated with an 8.73% higher likelihood of firm-level outsourcing and a 6.40% greater number of outsourcing events compared to an average F-S MMSA pair with a statistical significance at the 1% level. A similar increase in AT will increase the odds for fund-level outsourcing by 6.92% and the number of subcontracting events by 4.68%. It is worth mentioning that AT gains a larger economic magnitude with firm-level subcontracting. This finding further confirms the importance of proximity in asset delegation since firm-level deals involve more information collection and thus would be more responsive to a reduction in information costs. These findings hold when I use the log of departure flights to measure air travel because of the high passenger-flight correlation, shown in Table 3.

As shown in Panel C of Table 1, larger fund families tend to delegate portfolio management to subadvisors more. Arguably, large fund families tend to cluster in big cities, which are also better connected to other cities, so a potential concern is that previous findings are driven by a limited number of large fund cities. To deal with this concern, I first add the log of the sum of fund family size within fund MMSAs as an additional control variable and reestimate the regression (4). The results are displayed in Panel C of Table 4 and show that adding the log fund city family sizes in the specification does not absorb the effect of air traffic on new subcontracting activities between city pairs. Furthermore, I remove the top 3, top five, and top 10 fund MMSAs (measured by the number of fund families) in the sample and reestimate the regression (4) again. I report the estimates in Panel D of Table 4. The coefficient on AT remains positively significant, though the economic magnitude drops by 33%. The reduced economic magnitude reflects that, due to higher demand, mutual funds located in large fund cities are more responsive to changes in information costs when delegating portfolio management to subadvisors. The ubiquitous effect of AT on fund management subcontracting further pins down the AT effect of information costs reduction on fund management outsourcing.

[Insert Table 4 Here]

The results in Table 4 show that increased AT results in more fund management subcontracting. To further confirm the value of proximity, I test how AT affects subcontracting performance and report the results in Table 5. The basic insight here is that if higher AT reduces

the cost of information acquisition, newly subcontracted funds in response to higher AT should yield better performance. To test this performance impact, I use the specification below:

$$\text{Performance}_{i,j,t} = \beta * \text{AT}_{i,j,t-1} + \text{Controls}_{i,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t} \quad (5)$$

where $\text{Performance}_{i,j,t}$ is the performance of the newly formed fund-subadvisor pairs in year t identified as return improvements and future returns and $\text{Controls}_{i,t}$ denotes a vector of fund characteristics, including log of total net assets (fund size), fund management fees, and turnover. Other variables are the same as in (4). From specification (5), if there is no further clarification, the test samples only include actively managed equity funds, where information asymmetry issues between mutual funds and subadvisors are more severe. See Section 4.3 for more discussions on non-equity or non-active outsourced funds.

[Insert Table 5 Here]

Results of Table 5 show that the performance impact of AT is both statistically significant and economically sizable. Portfolio management subcontracts for active equity funds associated with a one-log-point higher AT exhibit higher annual performance of 3.90%, 3.80%, 4.8%, 3.60%, and 4.80% in terms of improvement in raw returns, excess returns, CAPM alphas, FF-3 alphas, and 4-Factor alphas, respectively. One may argue that the economic magnitude of AT on performance improvement can be partly attributed to the sample selection bias. Funds seeking new subadvisors may focus on realizing higher future returns, thus biasing the average performance improvement of these funds upwards. However, I do not believe that this concern is significant in my sample. In unreported statistics, the average annual performance improvement in excess returns and the CAPM alpha are 0.71% and 1.16%, respectively. Hence, although the sample means of performance improvement are positive, they are still much smaller than the economic magnitudes of AT. Results in Panel B show that the future returns also significantly go up as AT increases, and the economic significance of future performance is comparable to that of performance improvement. These findings confirm that the AT-induced performance improvement is not mainly driven by past underperformance or mean reversion. Taken together, the results in Table 5 lend support to my hypothesis that AT improves the efficiency of the market for fund management outsourcing by reducing information acquisition costs and improving the performance of sub-advised funds.

Mutual funds may also take advantage of proximity to better monitor subadvisors. Especially when sub-advised funds had inferior performance in the prior year, mutual funds will

have a stronger incentive to take advantage of increased proximity to monitor subadvisors, which should result in better performance. To test this hypothesis, I estimate the regression as in (6) using the sample of existing fund-subadvisor relationships:

$$\begin{aligned}
&\text{Performance}_{i,j,t} \\
&= \beta_1 * \text{AT}_{i,j,t} + \beta_2 * \text{Inferior}_{i,t-1} + \beta_3 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} + \text{Controls}_{i,t} \\
&+ \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{6}$$

where $\text{Performance}_{i,j,t}$ is the performance of the existing fund-subadvisor pairs in year t , identified as return improvements and current returns and $\text{Inferior}_{i,t-1}$ is the indicator of inferior fund performance in year $(t - 1)$, which is defined as negative CAPM alpha or below-median CAPM alpha. The variable of interest is the interaction between AT and the indicator of inferior past performance. If mutual funds take advantage of air traffic to better monitor subadvisors, one would expect a positive and significant β_3 .

[Insert Table 6 Here]

As displayed in Table 6, past inferior performance of sub-advised funds seems to give mutual funds a stronger incentive to take advantage of improved AT to monitor subadvisors' behavior since the estimates of β_3 in all the panels of Table 6 are positive and significant. As shown in the first two panels (A and B), a one log point increase in AT improves the performance of funds with inferior past performance by 0.16% per year in terms of 4-Factor alpha. This result is robust to whether inferior past performance is measured by a negative CAPM alpha or by a below-median CAPM alpha. Furthermore, the results in Panel C and Panel D suggest that the performance improvement is driven by better returns in the current period rather than the inferior past return, as a one log point increase in AT for underperforming funds makes the current 4-Factor alpha increase by 0.10% per year, accounting for 62.5% of the performance improvement.

According to Chevalier and Ellison (1999) and Chen, Hong, Jiang, and Kubik (2013), inferior past performance and higher idiosyncratic risk together will raise the probability of fund termination and hence exacerbate fund managers' career concerns. In addition, Chen, Hong, Jiang, and Kubik (2013) argue that the lack of soft information collection by mutual funds due to firm boundaries helps to explain the inferior performance of sub-advised funds (also through the channel of subadvisors' higher career concerns). Therefore, I allow AT to interact with the inferior

past performance indicator and the high past idiosyncratic risk indicator and conduct a series of tests using (7):

$$\begin{aligned}
& \text{Performance}_{i,j,t} \\
&= \beta_1 * \text{AT}_{i,j,t} + \beta_2 * \text{Inferior}_{i,t-1} + \beta_3 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&+ \beta_4 * \text{IdioRisk}_{i,t-1}^{\text{High}} + \beta_5 * \text{AT}_{i,j,t} * \text{IdioRisk}_{i,t-1}^{\text{High}} + \beta_6 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&* \text{IdioRisk}_{i,t-1}^{\text{High}} + \text{Controls}_{i,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{7}$$

where $\text{IdioRisk}_{i,t-1}^{\text{High}}$ is the indicator function denoting above-median idiosyncratic volatility measured by CAPM in the past year and other variables are the same as in (6). The estimate of interest in (7) is β_6 . A significantly positive estimate of β_6 implies that the previous performance improvement effect of AT is stronger for (or even fully driven by) career-concerned subadvisors, where mutual fund monitoring would play a more pronounced role.

To provide direct evidence of how mutual funds capitalize on improved proximity to conduct better monitoring, I regress subadvisors' idiosyncratic risk taking on AT (with interaction items) as specified in (8):

$$\begin{aligned}
\Delta \text{Epsilon}_{i,j,t} &= \beta_1 * \text{AT}_{i,j,t} + \beta_2 * \text{Inferior}_{i,t-1} + \beta_3 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&+ \beta_4 * \text{IdioRisk}_{i,t-1}^{\text{High}} + \beta_5 * \text{AT}_{i,j,t} * \text{IdioRisk}_{i,t-1}^{\text{High}} + \beta_6 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&* \text{IdioRisk}_{i,t-1}^{\text{High}} + \text{Controls}_{i,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{8}$$

where $\Delta \text{Epsilon}_{i,j,t}$ is the difference between the current year's idiosyncratic risk and the past year's idiosyncratic risk of the fund-subadvisor pair in year t and other variables are the same as in (6). As in (7), the estimate of interest in (7) is β_6 . Although a significant β_6 is necessary to support that mutual funds put more effort into monitoring more proximate, risk-concerned subadvisors, there is no straightforward prediction on the sign of β_6 since whether taking a higher idiosyncratic risk will lead to better performance is unclear. On one hand, Chen, Hong, Jiang, and Kubik (2013) argue that relatively low idiosyncratic risk taking plays a role in sub-advised funds' inferior performance. On the other hand, the literature on risk-shifting (e.g., Huang, Sialm, and Zhang, 2011; Lee, Patel, and Venkatesan, 2022) shows that increased (idiosyncratic) risk taking is

associated with lower future performance, although here $\Delta\text{Epsilon}_{i,j,t}$ measures the increase in risk taking on the yearly basis rather than the semi-yearly basis on which risk-shifting behaviors are measured. Therefore, to pin down the information costs reduction effect of AT, I need to show consistent results for the relation between fund performance and $\Delta\text{Epsilon}$ via estimating the model as specified in (9):

$$\begin{aligned}
&\text{Performance}_{i,j,t} \\
&= \beta_1 * \text{AT}_{i,j,t} + \beta_2 * \text{Inferior}_{i,t-1} + \beta_3 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&+ \beta_4 * \Delta\text{Epsilon}_{i,j,t} + \beta_5 * \text{AT}_{i,j,t} * \Delta\text{Epsilon}_{i,j,t} + \beta_6 * \text{AT}_{i,j,t} * \text{Inferior}_{i,t-1} \\
&* \Delta\text{Epsilon}_{i,j,t} + \text{Controls}_{i,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{9}$$

[Insert Table 7 Here]

The estimations of (7), (8), and (9) are reported in Table 7. From Panel A, one can see that the coefficient β_6 is significantly positive, and the parameter estimate of the previous variable of interest, the interaction item of AT and the indicator of past inferior performance, is no longer significant. Therefore, the preceding findings are driven by subadvisors with high career concerns, where the effect of reduced information costs is more pronounced. The economic magnitude of AT also gets stronger for high career-concern subadvisors in that a one log point increase in AT is associated with an increase in 4-Factor alpha by 0.34% per year, more than triple the magnitude as estimated in (6). The results in Panel B provide straightforward evidence on the channel through which mutual funds conduct monitoring. For career-concerned subadvisors, their increase of idiosyncratic risk goes down with AT, suggesting that mutual funds restrict the increase of idiosyncratic risk taking by subadvisors with inferior past performance and high past idiosyncratic risk. A one log point increase in AT will lead to a 0.05% greater decrease in the change of monthly 4-Factor idiosyncratic volatility for career-concerned subadvisors, accounting for 36.74% of the unconditional mean. Combining the findings of Panel A, the decreased change in idiosyncratic risk taking should help to explain subadvisors' performance improvement, and this is the case, as shown in Panel C: the estimates of the parameters of $\Delta\text{Epsilon}$ are all significantly negative, and if the subadvisor changes idiosyncratic volatility by one percentage point per month, the 4-Factor risk-adjusted return of the fund will drop by 0.72% per year. The results in Panel C further suggest that reducing the excessive increase of idiosyncratic risk taking is the driving factor for improved

performance for career-concerned subadvisors: a one log point increase in AT reduces the change of idiosyncratic risk taking by 0.05% per month, which will improve the current 4-Factor alpha by 0.04% per year, accounting for 12% of the total performance improvement due to greater proximity (0.34% per year for each one log point increase). Moreover, the empirical findings in Panel B and Panel C are consistent with Lee, Patel, and Venkatesan (2022), who document the strategic risk shifting by underperforming subadvisors are due to contract termination concerns.

4.2 Advisory Fee

In the market for delegated asset management, asset managers engage in marketing to reduce investors' information costs, and the marketing costs are compensated by investors (Sirri and Tufano, 1998; Hortaçsu and Syverson, 2004; Roussanov, Ruan, and Wei, 2021). Therefore, if AT saves information costs for investment companies, it saves subadvisors' marketing costs. As a result, the advisor should charge lower advisory fees. Following this insight, tests on whether AT increases are associated with reduced future advisory fees can provide further evidence of the effect of information costs on fund management outsourcing. Advisory fees in N-SAR B filings are reported with tiered structures, so I merge the fee structures with the CRSP fund total net assets data to estimate the advisory fees charged by subadvisors. I further construct F-S-year panel data and regress advisory fees on AT from the past year to conduct this series of tests. The regression is as follows:

$$\text{AdvisorFee}_{i,j,t} = \beta * \text{AT}_{i,j,t-1} + \text{Controls}_{i,t} + \tau_t + v_i + \phi_j + \varepsilon_{i,j,t} \quad (10)$$

where $\text{AdvisorFee}_{i,t}$ is the advisory fee of sub-advised funds i managed by subadvisor j disclosed in the N-SAR B filings year t ; $\text{Controls}_{i,t}$ denotes a vector of fund characteristics, including the past 12-month fund return and past 12-month fund flow. Fund flow is estimated based on current fund assets (TNA_t), prior fund assets (TNA_{t-1}), and current fund return (r_t) as:

$$\text{FundFlow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} * (1 + r_t)}{\text{TNA}_{i,t-1}}. \quad (11)$$

Fixed effects include year fixed-effects τ_t , fund fixed-effects v_i , and subadvisor fixed-effects ϕ_j .

Table 8 shows the regression results. The sample of Panel A includes all F-S relations, and the sample of Panel B only includes active equity funds under outsourced management. The coefficient estimates of AT are stable and statistically significant across all specifications after controlling for fund flows, performance based on various measures, and a set of fixed effects. The economic magnitude of reduced advisory fees is also significant compared to the annual marketing

costs of advisory firms. A one-log-point AT shock leads to a drop in the dollar value of advisory fees collected by each subadvisor by \$3,856.25. Data from some surveys suggest these numbers are nontrivial, although there is no public data about the annual marketing costs of investment advisors. For example, a 2022 survey by Broadridge shows that the average marketing budget for an advisory firm in 2019, 2020, and 2021 is \$19,100, \$12,900, and \$16,100, respectively.¹¹ These numbers suggest that the economic magnitude accounts for 24.01% of the annual marketing expenditure for an average financial advisor. Results in Panel B show that advisory fees increase as risk-adjusted return increases, consistent with skilled subadvisors collecting rents. However, the impact of AT on future advisory fees remains statistically significant even after controlling for risk-adjusted returns. Furthermore, for actively managed equity funds, where the information costs for subcontracting are likely to be higher, the saving of the dollar value advisory fees for each subadvisor due to increased AT jumps to \$5,663.64. This suggests that the value of proximity becomes greater when information costs are more binding. The tests in the following section will show the more pronounced effect of information costs on actively managed equity funds.

[Insert Table 8 Here]

4.3 Management Outsourcing with High Information Asymmetry

The effects of reduced information costs should be more binding when agents face more severe information asymmetry (Beatty and Harris, 1999; Krishnaswami and Subramaniam, 1999; Brown, Hillegeist, and Lo, 2004; Eleswarapu, Thompson, and Venkataraman, 2004). Consequently, if AT facilitates fund management outsourcing by reducing information costs, my findings should be more pronounced when the information asymmetry between fund companies and subadvisors is more severe. The complexities associated with active equity investment should make the subcontracting of active equity funds involve higher information costs. Therefore, I expect to see a greater impact on subcontracting events, performance improvement, and AT fee decreases in the subgroup of active equity funds.

Table 9 shows the comprehensive results on how the value of proximity varies with different degrees of information asymmetry. The first two columns of Panel A compare the economic magnitude of AT on subcontracting activities for active equity funds and non-active or passive equity funds. The comparison shows that the effect of AT on the former is twice as strong as the latter. The results of the last two columns suggest that, as AT increases, subcontracts for

¹¹ See <https://www.broadridge.com/assets/pdf/focused-on-growth-2022.pdf>

active equity funds or all equity funds also account for a higher proportion of the total new subcontracts observed between F-S MMSA pairs. This pattern indicates that the demand elasticity of proximity is higher for active equity fund management outsourcing, where F-S relations face a higher degree of information asymmetry. Panel B shows that, for the performance of new subcontracts for non-active-equity funds, there is no significant relation between AT and fund performance improvement. Given the easier information extraction between F-S relations for these funds, the value of proximity may play a less crucial role in outsourcing efficiency. The findings on the relation between AT and future advisory fees in Panel C echo the previous results: for non-active-equity funds, AT does not significantly reduce contract advisory fees due to lower information asymmetry between F-S relations in this niche market. Another finding in Panel C worth mentioning is that for non-active-equity funds, advisory fees go down as fund flow increases, which means that subadvisors can collect fewer rents for each dollar under their management when fund size increases. This finding is consistent with the lower managerial costs of these funds, whose asset growth would be more dependent on the distribution abilities of fund companies rather than the portfolio management skills of subadvisors. Thus, the lower bargaining power of subadvisors makes little room for rent collection. In sum, the results in Table 9 show that information asymmetry strengthens the effect of AT, further supporting the argument that increased proximity facilitates fund management outsourcing by lowering the information costs of investment companies.

[Insert Table 9 Here]

4.4 Robustness

The last part of this section is about the robustness test on the facilitating effect of AT on fund management outsourcing. Since passengers' travel decisions are not only influenced by the ease of travel but also influenced by unobservable, time-varying economic trends between the origin-destination city pairs, which are likely to also affect subcontracting events between the city pairs, using AT to identify information costs between mutual funds and subadvisors may suffer from endogeneity concerns. Therefore, using the introduction of new flights to identify the shocks for proximity updates in the spirit of Giroud (2013) should help further pin down the causal effect of AT on the efficiency of the market for fund management outsourcing. I apply the following identification strategy to redo the baseline analyses. Firstly, I identify the introduction of new direct flights during the sample period as the treatment, and following Ellis, Madureira, and

Underwood (2020), only treatments that bring more than 120 flights per year are identified.¹² Then, I set a three-year window to observe the treatment effect and estimate the regression as follows:

$$\text{SubcontractingEvents}_{i,j,t} = \beta * \text{Treatment}_{i,j,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t} \quad (12)$$

where $\text{SubcontractingEvents}_{i,j,t}$ denotes the new subcontracts between F-S MMSA pairs (i, j) in year t , and $\text{Treatment}_{i,j,t}$ equals 1 if there is an introduction of new flights (more than 120 flights) between F-S MMSA pairs (i, j) in the last one to three years, i.e., the post-event window lasts for three years. $\text{Treatment}_{i,j,t}$ equals 0 otherwise. Other variables are the same as in (3).

I also regress the performance of funds with subcontracting events on the treatment indicator variable in the spirit of (4). The idea here is that the new subcontracting events followed by the introduction of new flights should be motivated by better information and thus result in outperformance over other subcontracts. The regression is:

$$\text{Performance}_{i,j,t} = \beta * \text{Treatment}_{i,j,t} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t} \quad (13)$$

where $\text{Treatment}_{i,j,t}$ is defined in (12) with a post-event window of one year and all other variables are defined as in (5). The sample includes active equity funds only.

Further, I test the robustness of the previous findings that air travel improves the performance of underperforming sub-advised funds by repeating the test of (6) with the shock-based identification as in (13). The specification is as follows:

$\text{Performance}_{i,j,t}$

$$= \beta_1 * \text{Treatment}_{i,j,t} + \beta_2 * \text{Alpha}^-_{CAPM,i,(t-1)} + \beta_3 * \text{Alpha}^+_{CAPM,i,(t-1)} + \beta_4 * \text{Treatment}_{i,j,t} * \text{Alpha}^-_{CAPM,i,(t-1)} + \beta_5 * \text{Treatment}_{i,j,t} * \text{Alpha}^+_{CAPM,i,(t-1)} + \theta_{i,t} + \delta_{j,t} + \mu_{i,j} + \varepsilon_{i,j,t} \quad (14)$$

where $\text{Alpha}^-_{CAPM,i,(t-1)}$ and $\text{Alpha}^+_{CAPM,i,(t-1)}$ denote negative and positive past 12-month fund CAPM alphas, respectively, and all other variables are as in (13). Similar to (6), the variable of interest is the interaction between Treatment and the continuous measure of past inferior performance. A significantly negative estimate of β_4 implies that the introduction of new flights

¹² The earliest year for identifying new subcontracts is 2007, so the identification of new flights should be no earlier than 2006. Further, due to the consideration of parallel trend tests (up to three years before the introduction of new flights), the identification of new flights starts from 2009.

is associated with performance improvement for subadvisors with negative CAPM alphas in the past, as shown in Table 6.¹³

Table 10 reports the regression results. Panel A shows that the introduction of new flights significantly increases the subcontracting activities between the treated F-S MMSA pairs in the following three years. The economic magnitude of the shock is also very pronounced: the introduction of new flights leads to a 22.99% increase in subcontracting events relative to the mean, which is 5.33 times as large as that associated with a one log point increase in AT.¹⁴ Panel B shows that there is a parallel trend in management sub-advising activities between treated F-S MMSA pairs and control pairs before the shock. These results suggest that management subcontracting for active equity (AEQ) funds responds more strongly to the introduction of new flights. The estimation results in Panel C show that the performance improvement is significantly higher for subcontracting activities followed by the introduction of new flights. The economic magnitudes of the air traffic are more than two times those inferred from the estimates in Table 5. The estimates of β_4 in Panel D are significantly negative, as expected, providing robustness to the finding that mutual funds conduct better monitoring of subadvisors with bad past performance in response to improved proximity. The economic magnitude is also significant. For a loser subadvisor with an average negative past CAPM alpha (-0.30%), the treatment effect will lead to an increase of the current 4-Factor alpha by 0.20% per month, or 2.4% per year. Again, this economic magnitude is greater than the AT identification.

[Insert Table 10 Here]

The introduction of new air flights could be due to lobbying by the companies located in the origin-destination city pairs and thus subject to endogeneity concerns. Therefore, Giroud (2013) uses airlines' hub opening events to identify the exogenous variations in air travel, and this strategy, along with the airlines' hub opening data are used by Da, Gurun, Li, and Warachka (2019) for robustness tests. However, the hub opening events in Giroud (2013) are outcomes of the Airline Deregulation Act of 1978 and major U.S. airlines finished their hub-and-spoke reforms by the late 1990s. So, I cannot use the air hub opening events from Giroud (2013) for robustness tests due to the lack of overlap in the sample periods of the two studies.

¹³ In unreported results, the findings of Table 6 do not change when using continuous measurements of inferior (and superior) past fund performance.

¹⁴ Here the economic magnitude is based on the annual average of the shock-induced change in the [+1, +3] yearly window.

Therefore, to still find a hub-based identification of air travel in the spirit of Giroud (2013), I use Delta Air Lines closing their Dallas–Fort Worth airport hub (“DFW hub”) in 2004 as a quasi-natural experiment to conduct the second set of robustness tests. Before I elaborate on the details of the identification, I want to show the exogeneity of this identification by providing more details about this event.

Delta’s presence in DFW started as early as the middle 1970s. In 2004, Delta experienced the fourth consecutive year with substantial losses due to operation efficiency issues and high fuel prices. Besides, there were heavy debt maturities and pension obligations due in 2004, which deteriorated Delta’s financial situation. To improve operation efficiency and to relieve the financial stress, in September 2004, Delta began reconstructing the company to save operation costs, including closing the DFW hub, which would eliminate about 3,600 jobs. Therefore, the closing of Delta’s DFW airport hub in 2004 provides a quasi-natural experiment to study the causal effect of the value of proximity in mutual fund outsourcing.

What is worth noting is that there are a few other hub closing events from 2004 to 2014 (feasible for a [-3,3] Difference-in-Difference test in terms of the sample periods of my datasets), but none of them are as suitable for quasi-natural experiments as the 2004 DFW closing event. Firstly, some hub closing events are outcomes of mergers and acquisitions (M&A) by two airlines and thus are in effect hub “transferring” events, as the hubs just cease to be operated by the target firm and will still be under the acquirer/merger firm’s management after the M&A event.¹⁵ Secondly, the other hub closing events seem to be driven by reduced demand, such as US Airways’ closing of Pittsburgh (PIT) in 2004¹⁶ and American Airlines’ closing of St. Louis (STL) in 2009.¹⁷ While according to Delta’s 2004 annual report, the closing of DFW was not driven by reduced passengers (this is further confirmed by the parallel trend test results reported in Table 11).

I identify treated origin-destination city pairs as those seeing a 25% or higher drop in the number of air flights following the closing of the DFW airport hub in 2004 and redo test (12).¹⁸ Since the event year is 2004, the sample period of the test is between 2001 to 2007. All the fund-subadvisor relations are as reported in N-SAR B filings.

¹⁵ For example, US Airways ceased to run its Charlotte (CLT) hub in 2015, since it merged with American Airlines in the same year. CLT remained a hub in the newly formed airlines.

¹⁶ <https://www.bizjournals.com/pittsburgh/stories/2004/11/08/daily23.html>

¹⁷ <https://crankyflier.com/2009/09/18/american-kills-st-louis-strengthens-other-hubs/#comments>

¹⁸ The results of Table 11 remain if this restriction is relaxed. The least impacted city pairs witnessed a drop of 16% in flights after the dehubbing.

The estimates reported in Table 11 show the robustness of the baseline findings. After Delta's closing of the DFW hub in 2004, the treated origin-destination city pairs witness a significant drop in subcontracting activities in the following three years. Parallel trend test results also show that the findings are outcomes of the hub-closing event and not due to any previous trends. The economic magnitude of the air travel shock, in terms of new fund-level relationships, accounts for 57.02% of the unconditional annual mean (the average number in a [+1, +3] yearly window). The results of Table 10 and Table 11 also suggest that there is a symmetric effect of proximity in the fund management outsourcing market, which is consistent with the preceding findings based on AT.

[Insert Table 11 Here]

Lastly, I also conduct a set of placebo tests to further corroborate that increased AT helps mutual funds collect information on subadvisors and hence facilitates fund management outsourcing. If proximity facilitates the information collection of investment companies, then only the headquarters of fund companies and subadvisors connected by AT, as identified in the previous tests, should benefit from the reduction in information costs. Firstly, headquarters are known as the centers for decision-making, so outsourcing decisions should originate from the headquarters of investment companies. Second, headquarters have gathered information about a firm, and thus headquarters of subadvisors would be the most frequently visited by fund companies for collecting information. Therefore, I identify F-S MMSA pairs based on the location of the headquarters of both fund companies and subadvisors. Along this line, I design the placebo tests by assuming that AT that connects fund families and subadvisors differently would still predict future F-S subcontracting relations.

I construct three alternative F-S MMSA pairs. The first identification uses AT connections with the shortest geographical distance between fund company branch MMSAs and subadvisor headquarter MMSAs, i.e., Branch-Headquarter F-S MMSA pairs (BH F-S MMSA pairs). Data regarding the fund company branch MMSAs are from the address information of other business offices of fund advisors reported in Form ADV filings. The distances between fund company branches and subadvisor headquarters are from the National Bureau of Economic Research zip code distance data. The second identification follows a similar process, replacing MMSAs of fund company branches with those of subadvisor branches (from the address information of other business offices of subadvisors) and MMSAs of subadvisor headquarters with those of fund

company headquarters, i.e., Headquarter-Branch F-S MMSA pairs (HB F-S MMSA pairs). The third identification collects F-S MMSA pairs as reported in N-SAR filings, i.e., NSAR-Reported F-S MMSA pairs (NR F-S MMSA pairs). I identify the time series of AT for each of the alternative F-S MMSA pairs accordingly.

Then, I repeat the baseline analysis described in (4) using the three alternative identifications of F-S MMSA pairs and report the coefficients estimations in Table 12. The results suggest that the previously documented positive relation between AT and future subcontracting activities disappears when using non-headquarters-to-headquarters identifications of F-S MMSA pairs (and thus AT). Regressions based on NR-F-S MMSA pairs yield estimates relatively close to the baseline results because NR-F-S MMSA pairs may overlap with F-S MMSA pairs based on headquarters-to-headquarters identifications. The coefficient estimate is still not significant due to the noise in the identification, but the direction is expected. Therefore, placebo test results support the previous results that AT is a meaningful proxy for information costs, and increased AT helps reduce the costs for fund companies to collect information on subadvisors.

[Insert Table 12 Here]

5 Value of Proximity for Funds and Subadvisors

5.1 Value of Proximity for Funds: Determinants of Management Outsourcing Decisions and Subadvisor Turnovers

My results so far are all based on pairwise data, including F-S MMSA pairs and F-S pairs. The pair-level analyses are precise but may not provide the whole picture of whether funds respond to the reduced information costs. To shed light on the effect of reduction in information costs due to funds having better access to air travel, I use air travel at the fund MMSA level to model funds' outsourcing decisions and subadvisor turnover decisions. On the one hand, mutual funds may not assign a good subadvisor if the expected future performance improvement cannot cover the related information costs (Gârleanu and Pedersen, 2018). With the increased air travel at the fund MMSA level, however, non-local subadvisors become more geographically proximate than before, enabling fund companies to take advantage of the lowered information costs to learn about distant subadvisors. As a result, the reduced information acquisition cost makes it more likely that fund companies will delegate assets to these non-local subadvisors. On the other hand, when subadvisors become more accessible on account of improved air travel, it will be easier for mutual

funds to collect subadvisors' information. Since firm boundaries already make it a prior for mutual funds to impose high-powered incentives upon subadvisors (Chen, Hong, Jiang, and Kubik, 2013), the improved information acquisition by mutual funds will attenuate this issue by lowering either the odds of subadvisor turnover or the performance-termination sensitivity.

I use the aggregated departing air traffic (ADAT) defined in (2) to measure fund-level access to air travel. ADAT is the total air traffic departing from the focal fund company MMSA to all subadvisor MMSAs each year with a travelling distance longer than 100 miles. An increase in ADAT generates an exogenous improvement in fund companies' access to subadvisors in other MMSAs at an aggregated level, and the resulting reduction in information costs should increase the likelihood of establishing new management outsourcing relations between the focal investment company and non-local subadvisors. I test this hypothesis within the sample of active equity funds, where information costs are more relevant for fund management outsourcing.

The specification for estimating a fund's management outsourcing decision is:

$$DSA_{i,t} = \beta * ADAT_{i,t-1} + Controls_{i,t} + \tau_t + \theta_i + \varepsilon_{i,t} \quad (15)$$

where $DSA_{i,t}$ is the indicator whether the fund has a new distant subadvisor in year t and ADAT is defined as in (2). Controls are fund-year level control variables. τ_t and θ_i represents the year fixed effects and the fund MMSA fixed effects.

The specification for estimating funds' termination of subcontracting is:

$$Turnover_{i,t} = \beta * ADAT_{i,t-1} + Controls_{i,t} + \tau_t + \theta_i + \varepsilon_{i,t} \quad (16)$$

where $Turnover_{i,t}$ is the indicator of whether the fund has subadvisor turnover event in year t , the control variables are as in (15), and the interactions of ADAT and fund performance variables are also included.

Table 13 summarizes the results. First, I test whether ADAT can significantly predict future distant subcontracting activities (DSA) and report the findings in Panel A. DSA is defined as subcontracting between fund-subadvisor city pairs with a distance longer than 100 miles. The regression results suggest that ADAT is significantly associated with future management subcontracting in active equity funds, and a one log point increase in ADAT increases the outsourcing odds by 1%, accounting for 23.87% of the unconditional mean. Subsample test results further show that this finding is driven by an entry event, i.e., first-time fund management subcontracting. This is consistent with the thinking that information costs would be the highest for

first-time subcontracting, where value of proximity would be the most pronounced. These results support the hypothesis that proximity plays an important role in mutual funds' outsourcing decisions. Findings in Panel A also show that past performance (measured by FF-3 alpha) has a significant negative effect on DSA, which means that bad performance drives funds to incur the information costs of finding a new subadvisor. This finding echoes the theoretical arguments of Gârleanu and Pedersen (2018) that search costs are nontrivial to fund companies. The role played by fund size in funds' DSA decisions is more nuanced. On one hand, smaller funds tend to get into subcontracting, which is consistent with the summary statistics in Table 1. On the other hand, once funds get involved in management outsourcing, greater size facilitates future DSA decisions. This is also consistent with the predictions by Gârleanu and Pedersen (2018) that only large investors should conduct costly searches, because otherwise the search costs will not be fully compensated by an improvement in fund performance even if investors can find high-skill money managers.

[Insert Table 13 Here]

Panel B of Table 13 shows that subadvisor turnover is lower if the subadvisors are more accessible to fund companies due to increased air traffic. I find that subadvisor turnover is significantly associated with low past performance (measured by FF-3 alpha) and high portfolio turnover. I also find that fund asset growth is negatively related to subadvisor turnover, although the relation is not statistically significant. My major new finding is that air traffic significantly reduces the probability of subadvisor turnover. The estimates from all the models are significant at the level of 1%. A one log point increase in ADAT reduces the turnover odds in the following year by 0.3%, accounting for 2.39% of the unconditional mean. The estimation of the interaction item between ADAT and fund performance is positive, though not significant, which suggests that ADAT also attenuates the higher performance-turnover sensitivity faced by subadvisors (Chen, Hong, Jiang, and Kubik, 2013).

5.2 Value of Proximity for Subadvisors: Delegated Asset Management Business and Air Traffic to Subadvisor MMSA

My last set of tests aims to provide evidence on the effect of information costs from the subadvisor side. In the previous section, I have shown that an increase in air travel significantly reduces advisory fees, and the economic magnitudes are comparable to those of advisors' marketing costs. In this section, I test how increased proximity leads subadvisors to gain delegated

asset management business from fund companies. I also aim to provide more evidence on the impact of information cost reductions on the efficiency of the sub-advising market.

I measure the size of the outsourcing fund management business as the log number of investment firms (CIKs) that delegate fund assets to a subadvisor's management and as the log number of funds under the subadvisor's management. The exogenous changes in proximity are measured by the subadvisor MMSA level AT, aggregated arriving air traffic, AAAT, as in (3). Only flights with distances longer than 100 miles are counted in AAAT. I use the weighted average FF-3 alpha of all active equity funds under advisors' management as a proxy for total returns. As for control variables, I measure the size of a subadvisor using the total assets at its full disposal as reported in Form ADV. I also measure the years an advisory firm has worked as a subadvisor as its experience in the fund management outsourcing industry. If the advisory firm worked as a subadvisor in 1996, when the NSAR-B filings are available for the first time, I use 1996 as the starting year to compute the advisory firm's experience. Interaction terms between AAAT, and performance/subadvisor size/experience are also included in the tests. If air traffic helps subadvisors gain business from fund companies, I expect a significant and positive coefficient on AAAT. The model specification is as follows:

$$\text{SubcontractingBusiness}_{j,t} = \beta * \text{AAAT}_{i,j,t-1} + \text{Controls}_{j,t} + \tau_t + \delta_j + \phi_j + \varepsilon_{j,t} \quad (17)$$

where $\text{SubcontractingBusiness}_{j,t}$ is the number of mutual funds that hire the focal subadvisor for portfolio management outsourcing in year t . AAAT is defined as in (3). $\text{Controls}_{j,t}$ denotes the vector of a series of subadvisor-year level control variable, and τ_t , δ_j , and ϕ_j are the year fixed effects, the subadvisor MMSA fixed effects, and the subadvisor fixed effects, respectively.

[Insert Table 14 Here]

The results are reported in Table 14. I find that identifications without interactions do not show that past AAAT can introduce more delegated fund management for a subadvisor. However, after controlling the interaction item of AAAT and subadvisor size, AAAT itself has a very significant effect on gaining outsourced fund management business. Each one log point increase in AAAT is associated with an increase of 0.347 log point in firm-level delegations, accounting for 24.22% of the unconditional mean. The statistical significance of AAAT reduces a little, but the economic magnitude remains comparable when using the log number of funds as the measurement of fund delegation business. As a proxy for reputation, the subadvisor size plays a

crucial role in gaining business in the fund management outsourcing industry. The estimates for subadvisor size are all highly significantly positive across all the specifications, but they become much greater after including its interaction with AAAT. This is consistent with the intuition that both AAAT and subadvisor size play a role in reducing information costs. So, both AAAT and subadvisor size should have a significant positive effect, and their interaction term should have a negative effect due to the substitution effect. I also find that past performance plays a significant role in gaining more fund outsourcing business, and still due to the substitution effect of AAAT and performance in terms of reducing information costs, the interaction item between them is significantly negative.

6 Conclusion

In this paper, I study how information costs affect fund management outsourcing activities and the sub-advising market efficiency. I exploit the exogenous variation in the information costs caused by increased air travel connecting mutual fund cities and subadvisor cities to make causal inferences about the value implications of proximity for subcontracting activities and sub-advised fund performance. I first empirically show that investment company–subadvisor city pairs experience significantly more subcontracting events following increases in air traffic and that fund subcontracting efficiency is improved by reductions in air travel–induced information costs. In addition, I find that subadvisors charge lower advisory fees after an increase in air traffic. Further, I show that the performance improvement of sub-advising is mainly driven by outsourcing subcontracts for active equity funds, where high information asymmetry makes fund companies more responsive to a reduction in information costs. To show the robustness of my findings, I rely on the introduction of new flights as another identification strategy to further confirm that increased air travel is associated with more subcontracting activities between treated fund company–subadvisor city pairs. I also use the 2004 Delta Air Lines’ closing of their DFW hub as a quasi-natural experiment to provide empirical evidence on the causal effect of air traffic on subcontracting connections. Furthermore, placebo test results suggest that only headquarters-to-headquarters proximity improvements increase future subcontracting activities between the fund-subadvisor city pairs involved.

In addition to conducting city pair and fund-subadvisor pair analyses, I also explore the value implications of proximity for funds and subadvisors, respectively. Tests on funds’ access to

air travel indicate that mutual fund companies respond to the reduction in information costs. An increase in the aggregated air traffic to all subadvisor cities increases the odds of local fund companies' entering management subcontracts with non-local subadvisors, and the turnover of the existing subadvisors accordingly decreases. Tests on subadvisors' access to air travel indicate that subadvisors also benefit from the reduced information costs due to increased aggregated air traffic from all fund company cities, which helps local subadvisors gain more delegated asset management business from fund companies. In sum, the findings of this paper show that geographical proximity plays a significant role in the mutual fund management outsourcing market.

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Table 1: Management Outsourcing in the Mutual Fund Market

This table reports features of the market for fund management outsourcing from 2006 to 2017. Outsourced funds are funds with unaffiliated subadvisors. The number of outsourced funds and the percentage of outside funds of all active funds each year are reported at both the fund level and the fund-family level in Panel A. Panel B reports the fundamental characteristics of in-house and outsourced funds, respectively. The comparisons of fundamentals at the fund-family level are reported in Panel C. Fund identifiers are the series CIKs in the EDGAR database, and fund family identifiers are the advisor CIKs in N-SAR B filings. Data on fund returns and other characteristics are from the CRSP Survivor-Bias-Free US Mutual Fund Database. Active funds are funds with empty values in CRSP Index Fund Flag and ETF-ETN Flag.

Panel A: Fraction of Outsourced Funds by Year

	All Funds	Outsourced Funds	Active Funds	Active Outsourced Funds	Fund Family	Fund Family with Subadvisors
2006	2512	695 (27.66%)	2436	679 (27.87%)	279	130 (46.59%)
2007	2863	793 (27.69%)	2765	770 (27.84%)	278	126 (45.32%)
2008	3315	875 (26.39%)	3017	823 (27.27%)	314	143 (45.54%)
2009	3708	1009 (27.21%)	3316	940 (28.34%)	337	141 (41.83%)
2010	3975	1088 (27.37%)	3547	1006 (28.36%)	346	134 (38.72%)
2011	4324	1194 (27.61%)	3885	1102 (28.36%)	392	148 (37.75%)
2012	4597	1265 (27.51%)	4125	1172 (28.41%)	427	158 (37.00%)
2013	4963	1321 (26.61%)	4421	1207 (27.30%)	461	162 (35.14%)
2014	5417	1411 (26.04%)	4818	1280 (26.56%)	523	179 (34.22%)
2015	5658	1438 (25.41%)	5043	1300 (25.77%)	573	183 (31.93%)
2016	6104	1605 (26.29%)	5371	1445 (26.90%)	612	197 (32.18%)
2017	6296	1592 (25.28%)	5525	1391 (25.17%)	622	196 (31.51%)
Average	4478	1191 (26.59%)	4022	1093 (27.17%)	430	158 (36.74%)

Panel B: Features of In-House and Outsourced Funds

	Fund Types					
	In-house	Outsourced	Active In-house	Active Outsourced	Passive In-house	Passive Outsourced
Age	13.32	10.66	13.92	10.85	8.48	8.51
TNA (\$ Mil.)	1739.27	887.05	1815.61	878.69	1135.45	969.64
Mgmt. Fee	0.55%	0.72%	0.57%	0.75%	0.41%	0.46%
Turnover	0.88	1.00	0.87	0.98	1.00	1.16
12b-1 Fee	0.71%	0.68%	0.72%	0.68%	0.57%	0.71%
Avg. #Obs. Fund/Year	3287.16	1190.5	2929.5	1092.92	357.67	97.58

Panel C: Features of Fund Families with/without Outsourced Funds

	Fund Family without Outsourced Funds	Fund Family with Outsourced Funds	Diff. (t-statistics)
Age	16.64	22.52	11.16
TNA (\$ Mil.)	12560.89	22205.85	4.58
Mgmt. Fee	0.75%	0.73%	-2.43
Turnover	0.88	0.96	1.99
12b-1 Fee	0.48%	0.65%	12.7
Number of Funds	4.48	21.27	30.32
Ratio of Active Funds	96.27%	92.39%	-7.27
Avg. #Obs. Fund Family/Year	272.25	158.08	

Table 2: Outsourcing/Flight Connections between Fund-Subadvisor (F-S) MMSA Pairs

Table 2 reports the summary statistics on air travel data and subcontracting events. The sample period of the statistics of air travel is from 2005 to 2016 (one year earlier than the start and end points of the sample period). The table displays the number of fund MMSAs and subadvisor MMSAs, the number of all the possible links between different MMSAs, the number of F-S MMSA pairs with management subcontracting relations, the number of MMSA-level flight connections, and the coverage ratios of subcontracting relations and flight connections between different MMSAs are reported in parentheses. The flight connections and the corresponding coverage ratios here are one-year lag values. The correlation between subcontracting connections and last-year flight connections is reported at the bottom of the table with *p*-statistics in parentheses.

	Fund MMSA	Subadvisor MMSA	Total Connections	Subcontract Connections	Last-Yr. Flight Connections
2006	62	92	5665	443 (7.82%)	846 (14.93%)
2007	58	90	5183	421 (8.12%)	794 (14.55%)
2008	58	93	5357	450 (8.4%)	859 (15.23%)
2009	56	96	5338	453 (8.49%)	840 (17.55%)
2010	50	96	4766	431 (9.04%)	768 (15.61%)
2011	50	96	4765	439 (9.21%)	760 (15.13%)
2012	49	95	4620	439 (9.50%)	727 (16.41%)
2013	48	92	4379	414 (9.45%)	728 (15.78%)
2014	48	95	4524	426 (9.42%)	797 (16.38%)
2015	47	95	4431	446 (10.07%)	821 (18.91%)
2016	47	93	4336	462 (10.65%)	844 (19.40%)
2017	50	95	4711	427 (9.06%)	875 (19.70%)
Average	51.92	94	4839.58	437.58 (9.10%)	804.92 (16.63%)
Correlation of Coverage Ratios					0.6428 (0.0242)

Table 3: Summary Statistics

Table 3 reports the summary statistics for air travel and the management outsourcing event data. The sample period for air travel data (including AT and the number of flights) is 2006–2016, and the sample period for new subcontracting events is 2007–2017. Panel A reports the summary statistics of departing passengers and the number of departure flights from fund MMSAs. Panel B displays the summary statistics of subcontracting activities between fund MMSAs and Subadvisor MMSAs across the years.

Panel A: Statistics on Air Travel

	25% Pctl	50% Pctl	75% Pctl	Mean	Std Dev
Number of Passengers	9111	98842	311636	220384	303605.2
Departure Flights	142	1384	3190	2340.77	2915.74
Correlation		0.9289 (0.0000)			
#Obs. Fund-MMSA-Year		8011			

Panel B: Statistics on Management Subcontracting

Year	F-S MMSA	I (Firm-Level Subcontracts)	I (Fund-Level Subcontracts)	N (Firm-Level Subcontracts)	N (Fund-Level Subcontracts)
2007	5183	125	166	251	392
2008	5357	156	203	310	423
2009	5338	116	160	257	390
2010	4766	113	140	237	307
2011	4765	114	144	255	321
2012	4620	135	161	245	356
2013	4379	86	115	142	208
2014	4524	126	150	244	284
2015	4431	134	155	303	383
2016	4336	118	148	246	363
2017	4711	82	108	154	228
Average	4764.55	118.64 (2.29%)	150 (2.89%)	240.36 (4.69%)	332.27 (6.41%)

Table 4: Baseline Results

Table 4 shows the coefficient estimates of the model based on F-S-MMSA-year panel data as identified in (4). New subcontracts are counted as both indicators (I) and numbers (N) at the firm level (Panel A) and fund level (Panel B). The independent variable is past-year air traffic (AT) as defined in (1) or past-year log number of departure flights from fund MMSAs. The variables are winsorized at 1%, and the standard errors are clustered at the F-S MMSA level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Subcontracting Events at Firm Level

	(1)	(2)	(3)	(4)
	I (New Firm- Level Relations)	N (New Firm- Level Relations)	I (New Firm- Level Relations)	N (New Firm- Level Relations)
AT_{t-1}	0.002*** [3.546]	0.003*** [3.601]		
$\text{Log Departure Flights}_{t-1}$			0.004*** [3.498]	0.006*** [3.644]
FundMSA*Year FE	Yes	Yes	Yes	Yes
SubadvMSA*Year FE	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes
R-squared	0.381	0.423	0.381	0.423
#Obs. F-S-MMSA-Year	52,033	52,033	52,033	52,033

Panel B: Subcontracting Events at Fund Level

	(1)	(2)	(3)	(4)
	I (New Fund- Level Relations)	N (New Fund- Level Relations)	I (New Fund- Level Relations)	N (New Fund- Level Relations)
AT_{t-1}	0.002*** [3.298]	0.003*** [3.683]		
$\text{Log Departure Flights}_{t-1}$			0.005*** [3.912]	0.007*** [4.107]
FundMMSA*Year FE	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes
R-squared	0.427	0.473	0.427	0.473
#Obs. F-S-MMSA-Year	52,033	52,033	52,033	52,033

Panel C: Fund City Family Size

	N (New Firm-Level Relations)	N (New Fund-Level Relations)
AT_{t-1}	0.003*** [3.093]	0.003*** [3.439]
$Log(FundCityFamilySize)_t$	-0.000 [-0.410]	-0.001 [-0.956]
SubadvMMSA*Year FE	Yes	Yes
FS-MMSA Pair FE	Yes	Yes
R-squared	0.427	0.476
#Obs. FS-MMSA-Year	40,777	40,777

Panel D: Regression Sample with Top Fund Cities Removed

	N (New Firm-Level Relations) (Top 3 fund cities removed)	N (New Firm-Level Relations) (Top 5 fund cities removed)	N (New Firm-Level Relations) (Top 10 fund cities removed)
AT_{t-1}	0.002*** [3.230]	0.002*** [3.332]	0.002*** [3.359]
FundMMSA*Year FE	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes
R-squared	0.352	0.353	0.325
#Obs. FS-MMSA-Year	48,949	46,893	41,753

Table 5: Performance of New Subcontracts

Table 5 shows the coefficient estimates of the F-S-year panel regression as identified in (5). Only newly formed outsourcing relations for active equity funds are included (“subcontracting events”). The dependent variable in Panel A is the return difference before and after the subcontracting events (i.e., the performance improvement). In Panel B, the dependent variable is the fund performance one year after the subcontracting events. Return measures include 12-month raw returns, 12-month excess returns, one-year CAPM alphas, one-year Fama-French three-factor (FF-3) alphas, and one-year Carhart four-factor (4-Factor) alphas. *AT* is air traffic as defined in (1). *Fund Size* is the log of CRSP fund total net assets. *Mgmt. Fee* is the CRSP fund management fee (as in percentage numbers). *Turnover* is the CRSP fund annual turnover. The variables are winsorized at 1%, and the standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Performance Improvement

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_{t-1}	0.039** [2.378]	0.038** [2.412]	0.004*** [4.013]	0.003* [1.960]	0.004*** [2.959]
$Fund\ Size_t$	-0.003 [-0.847]	-0.003 [-0.837]	-0.001* [-1.854]	-0.0004* [-1.850]	-0.0004* [-1.662]
$Mgmt.\ Fee_t$	0.003 [0.128]	0.004 [0.147]	0.000 [0.194]	0.001 [0.821]	0.001 [0.849]
$Turnover_t$	-0.005 [-0.336]	-0.005 [-0.344]	-0.001* [-1.858]	-0.001*** [-2.869]	-0.001** [-2.383]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.942	0.941	0.530	0.647	0.608
#Obs. Subcontracting Events	729	729	729	729	729

Panel B: Future Performance

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_{t-1}	0.026*** [3.953]	0.026*** [3.946]	0.005*** [4.321]	0.004*** [8.515]	0.005*** [8.678]
$Fund\ Size_t$	-0.001 [-0.243]	-0.001 [-0.244]	-0.000 [-1.095]	-0.000 [-1.492]	-0.000 [-1.628]
$Mgmt.\ Fee_t$	-0.006 [-0.285]	-0.006 [-0.276]	-0.001 [-0.333]	0.000 [0.222]	0.001 [0.562]
$Turnover_t$	-0.012 [-0.932]	-0.012 [-0.937]	-0.001 [-0.613]	-0.001 [-0.975]	-0.001 [-1.201]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.923	0.925	0.483	0.551	0.549
#Obs. Subcontracting Events	729	729	729	729	729

Table 6: Performance of Existing Subcontracts

Table 6 shows the coefficient estimates of the model based on fund-subadvisor-year panel data as identified in (6). Only existing outsourcing relations for active equity funds are included. The dependent variables in Panel A and Panel B are the change in fund return between the current year and the past year. In Panel A and Panel B, the measure of inferior past performance is the indicator of negative past 12-month capital asset pricing model (CAPM) alpha and the indicator of below-median past 12-month CAPM alpha, respectively. The dependent variables in Panel C and Panel D are the change in fund return between the current year and the past year. In Panel C and Panel D, the measure of inferior past performance is the indicator of negative past 12-month CAPM alpha and the indicator of below-median past 12-month CAPM alpha, respectively. Performance measures in percentage include 12-month raw returns, 12-month excess returns, one-year CAPM alphas, one-year Fama-French three-factor (FF-3) alphas, and one-year Carhart four-factor (4-Factor) alphas. *AT* is air traffic as defined in (1). $I(Alpha_{CAPM}^-)$ is an indicator function of negative fund CAPM alpha. $I(Alpha_{CAPM}^{Loser})$ is an indicator function of below-median fund CAPM alpha. *Fund Size* is the log of CRSP fund total net assets. *Mgmt. Fee* is the CRSP fund management fee (in percentage). *Turnover* is the CRSP fund annual turnover. The variables are winsorized at 1%, and the standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Performance Improvement – Negative CAPM Alpha as Inferior Past Performance

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_t	0.001	0.001	0.009	-0.011	-0.016
	[0.007]	[0.008]	[0.769]	[-1.058]	[-1.452]
$I(Alpha_{CAPM, t-1}^-)$	10.093***	10.046***	0.882***	0.456***	0.434***
	[15.259]	[15.207]	[15.019]	[8.056]	[7.245]
$AT_t * I(Alpha_{CAPM, t-1}^-)$	0.104	0.104	0.008	0.012**	0.013*
	[1.534]	[1.537]	[1.247]	[1.986]	[1.949]
$Fundsize_t$	-0.042	-0.042	-0.008	-0.011*	-0.013**
	[-0.529]	[-0.522]	[-1.311]	[-1.910]	[-2.208]
$Managementfee_t$	-0.067	-0.055	0.025	0.016	0.023
	[-0.149]	[-0.122]	[0.685]	[0.652]	[0.743]
$Turnover_t$	-0.399	-0.404	-0.053**	-0.038***	-0.042**
	[-1.215]	[-1.238]	[-2.300]	[-2.773]	[-2.396]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.871	0.869	0.487	0.422	0.432
#Obs. FS-MMSA-Year	5,934	5,934	5,934	5,934	5,934

Panel B: Performance Improvement – Below-Median CAPM Alpha as Inferior Past Performance

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_t	0.095 [0.668]	0.095 [0.668]	0.018* [1.688]	-0.004 [-0.419]	-0.009 [-0.851]
$I(Alpha_{CAPM}^{Loser}, t-1)$	9.834*** [17.906]	9.796*** [17.893]	0.851*** [18.478]	0.478*** [9.731]	0.487*** [8.747]
$AT_t * I(Alpha_{CAPM}^{Loser}, t-1)$	0.120** [1.994]	0.120** [1.991]	0.006 [1.228]	0.012** [2.163]	0.013** [1.968]
$Fundsize_t$	0.053 [0.643]	0.053 [0.649]	0.0001 [0.017]	-0.005 [-0.987]	-0.008 [-1.304]
$Managementfee_t$	0.730 [1.462]	0.739 [1.482]	0.093** [2.406]	0.059** [2.239]	0.066** [2.014]
$Turnover_t$	-0.713** [-2.128]	-0.717** [-2.147]	-0.080*** [-3.236]	-0.054*** [-3.689]	-0.058*** [-3.024]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.873	0.872	0.487	0.439	0.451
#Obs. FS-MMSA-Year	5,934	5,934	5,934	5,934	5,934

Panel C: Current Performance – Negative Return as Inferior Past Performance

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_t	0.037 [0.278]	0.039 [0.295]	0.009 [0.892]	0.011 [1.215]	0.008 [0.882]
$I(Alpha_{CAPM, t-1}^-)$	1.133* [1.804]	1.127* [1.799]	0.077* [1.775]	-0.073* [-1.902]	-0.065 [-1.572]
$AT_t * I(Alpha_{CAPM, t-1}^-)$	0.143** [2.573]	0.142** [2.570]	0.010** [2.383]	0.011*** [2.784]	0.010** [2.431]
$Fundsize_t$	0.133 [1.417]	0.133 [1.418]	0.004 [0.663]	-0.007 [-1.015]	-0.010 [-1.353]
$Managementfee_t$	-1.439*** [-2.775]	-1.438*** [-2.778]	-0.084** [-1.991]	-0.103** [-2.472]	-0.121*** [-2.863]
$Turnover_t$	-1.012*** [-3.880]	-1.008*** [-3.886]	-0.008 [-0.334]	-0.009 [-0.380]	-0.008 [-0.333]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.814	0.817	0.345	0.356	0.364
#Obs. FS-MMSA-Year	5,934	5,934	5,934	5,934	5,934

Panel D: Current Performance – Below-Median Return as Inferior Past Performance

	(1)	(2)	(3)	(4)	(5)
	Raw Return	Excess Return	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_t	0.079 [0.624]	0.081 [0.642]	0.013 [1.344]	0.013 [1.538]	0.011 [1.167]
$I(Alpha_{CAPM}^{Loser}, t-1)$	0.993** [2.143]	0.992** [2.153]	0.098*** [2.734]	-0.030 [-1.022]	-0.011 [-0.350]
$AT_t * I(Alpha_{CAPM}^{Loser}, t-1)$	0.137*** [3.240]	0.136*** [3.237]	0.008** [2.081]	0.010*** [2.905]	0.009*** [2.596]
$Fundsize_t$	0.154 [1.639]	0.154 [1.639]	0.006 [0.899]	-0.006 [-0.908]	-0.009 [-1.234]
$Managementfee_t$	-1.244** [-2.453]	-1.243** [-2.457]	-0.070* [-1.701]	-0.098** [-2.416]	-0.116*** [-2.816]
$Turnover_t$	-1.087*** [-4.103]	-1.084*** [-4.110]	-0.013 [-0.560]	-0.010 [-0.432]	-0.009 [-0.381]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.814	0.817	0.345	0.357	0.366
#Obs. FS-MMSA-Year	5,934	5,934	5,934	5,934	5,934

Table 7: Subadvisor Career Concern and Performance of Existing Subcontracts

Table 7 shows the coefficient estimates of the model based on fund-subadvisor (F-S) year panel data as identified in (7), (8), and (9). Only existing outsourcing relations for active equity funds are included. Panel A shows the estimates of the specification (7). The dependent variables in Panel A are risk-adjusted returns in the current year. Percentage return measures include one-year CAPM alphas, one-year Fama-French three-factor (FF-3) alphas, and one-year Carhart four-factor (4-Factor) alphas. Panel B shows the estimates of the specification (8). The dependent variables in Panel B are the percentage numbers of the change of fund idiosyncratic risk between the current year and the prior year. The models for estimating idiosyncratic risks are CAPM, FF-3 model, and 4-Factor model. Panel C shows the estimates of the specification (9). The dependent variables are the same as in Panel A. $\Delta Epsilon_{i,j,t}^{CAPM}$, $\Delta Epsilon_{i,j,t}^{FF-3}$, and $\Delta Epsilon_{i,j,t}^{4-Factor}$ denote the changes in fund idiosyncratic risk based on residuals of the CAPM regression model, FF-3 regression model, and 4-Factor regression model, respectively. AT is air traffic as defined in (1). $I(Alpha_{CAPM}^-)$ is an indicator function of negative fund CAPM alpha. $I(Idio_{CAPM}^{High})$ is an indicator function of above-median past 12-month fund idiosyncratic volatility derived from the CAPM regression model. $Fund\ Size$ is the log of CRSP fund total net assets. $Mgmt.Fee$ is the CRSP fund management fee (in percentage). $Turnove$ is the CRSP fund annual turnover. The variables are winsorized at 1%, and the standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Future Performance of Career-Concerned Subadvisor

	(1)	(2)	(3)
	CAPM Alpha	FF-3 Alpha	4-Factor Alpha
AT_t	0.013 [1.323]	0.015* [1.730]	0.013 [1.361]
$I(Alpha_{CAPM, t-1}^-)$	0.131*** [3.100]	0.072* [1.812]	0.079* [1.816]
$AT_t * I(Alpha_{CAPM, t-1}^-)$	-0.001 [-0.195]	-0.003 [-0.644]	-0.004 [-0.866]
$I(Idio_{CAPM, t-1}^{High})$	-0.002 [-0.035]	0.048 [0.810]	0.040 [0.656]
$AT_t * I(Idio_{CAPM, t-1}^{High})$	-0.015** [-2.451]	-0.016*** [-2.932]	-0.016*** [-2.775]
$I(Alpha_{CAPM, t-1}^-)$ $* I(Idio_{CAPM, t-1}^{High})$	-0.100 [-1.162]	-0.275*** [-2.778]	-0.272*** [-2.595]
$AT_t * I(Alpha_{CAPM, t-1}^-)$ $* I(Idio_{CAPM, t-1}^{High})$	0.022*** [2.957]	0.027*** [3.051]	0.028*** [3.011]
$Fundsize_t$	0.001 [0.187]	-0.011 [-1.636]	-0.014* [-1.952]
$Managementfee_t$	-0.022 [-0.941]	-0.029 [-1.297]	-0.028 [-1.230]
$Turnover_t$	-0.060 [-1.463]	-0.066* [-1.688]	-0.084** [-2.117]
FundMMSA*Year FE	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes
R-squared	0.349	0.363	0.371
#Obs. FS-MMSA-Year	5,934	5,934	5,934

Panel B: Idiosyncratic Risk Taking of Career-Concerned Subadvisors

	(1)	(2)	(3)
	CAPM Epsilon	FF-3 Epsilon	4-Factor Epsilon
AT_t	-0.029 [-1.007]	-0.012 [-0.453]	-0.015 [-0.581]
$I(\text{Alpha}_{CAPM}^-, t_{-1})$	-0.106 [-0.527]	-0.179 [-0.951]	-0.188 [-1.072]
$AT_t * I(\text{Alpha}_{CAPM}^-, t_{-1})$	0.004 [0.235]	0.004 [0.230]	0.009 [0.552]
$I(\text{Idio}_{CAPM}^{High}, t_{-1})$	-0.868*** [-3.376]	-1.050*** [-5.126]	-0.989*** [-5.246]
$AT_t * I(\text{Idio}_{CAPM}^{High}, t_{-1})$	0.044* [1.891]	0.032* [1.677]	0.040** [2.241]
$I(\text{Alpha}_{CAPM}^-, t_{-1})$ $* I(\text{Idio}_{CAPM}^{High}, t_{-1})$	-0.356 [-1.223]	0.433* [1.673]	0.686*** [2.725]
$AT_t * I(\text{Alpha}_{CAPM}^-, t_{-1})$ $* I(\text{Idio}_{CAPM}^{High}, t_{-1})$	-0.060** [-2.223]	-0.036 [-1.530]	-0.050** [-2.168]
$Fundsize_t$	0.057*** [2.772]	0.052*** [2.719]	0.036* [1.719]
$Managementfee_t$	0.003 [0.046]	0.075 [1.232]	0.013 [0.163]
$Turnover_t$	0.042 [0.378]	-0.025 [-0.266]	0.016 [0.124]
FundMMSA*Year FE	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes
R-squared	0.431	0.454	0.432
#Obs. FS-MMSA-Year	5,934	5,934	5,934

Panel C: Idiosyncratic Risk Taking and Performance of Sub-advised Fund

	(1) CAPM Alpha	(2) FF-3 Alpha	(3) 4-Factor Alpha
AT_t	0.008 [0.896]	0.011 [1.288]	0.008 [0.882]
$I(\text{Alpha}_{CAPM, t-1}^-)$	0.059 [1.457]	-0.071* [-1.900]	-0.069 [-1.610]
$AT_t * I(\text{Alpha}_{CAPM, t-1}^-)$	0.008** [2.068]	0.010*** [2.633]	0.009** [2.223]
$\Delta\text{Epsilon}_{i,j,t}^{CAPM}$	-0.089*** [-5.235]		
$AT_t * \Delta\text{Epsilon}_{i,j,t}^{CAPM}$	0.001 [0.637]		
$I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{CAPM}$	0.039** [2.087]		
$AT_t * I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{CAPM}$	-0.002 [-1.107]		
$\Delta\text{Epsilon}_{i,j,t}^{FF-3}$		-0.051*** [-3.154]	
$AT_t * \Delta\text{Epsilon}_{i,j,t}^{FF-3}$		-0.001 [-0.447]	
$I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{FF-3}$		0.011 [0.685]	
$AT_t * I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{FF-3}$		-0.000 [-0.224]	
$\Delta\text{Epsilon}_{i,j,t}^{FF-4}$			-0.061*** [-3.736]
$AT_t * \Delta\text{Epsilon}_{i,j,t}^{FF-4}$			-0.001 [-0.490]
$I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{FF-4}$			0.031 [1.645]
$AT_t * I(\text{Alpha}_{CAPM, t-1}^-) * \Delta\text{Epsilon}_{i,j,t}^{FF-4}$			0.000 [0.158]
Fundsize_t	0.011* [1.654]	-0.002 [-0.361]	-0.006 [-0.812]
Managementfee_t	0.005 [0.218]	0.002 [0.088]	-0.003 [-0.120]
Turnover_t	-0.104** [-2.564]	-0.117*** [-2.820]	-0.133*** [-3.258]
FundMMSA*Year FE	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes
FS-MMSA Pair FE	Yes	Yes	Yes
R-squared	0.377	0.374	0.381
#Obs. FS-MMSA-Year	5,934	5,934	5,934

Table 8: Information Costs and Advisory Fees

Table 8 reports the regression estimates on the effect of air traffic (AT) on future advisory fees based on fund-subadvisor year panel data of the full sample and the sample of active equity funds as modeled in (10). The dependent variable is the advisory fee, and the independent variables are lagged by one year. Advisory fees are percentage numbers computed based on the tiered structures in N-SAR B filings and the CRSP fund total net assets. Panel A reports the regression results based on the full sample of sub-advised funds, and Panel B reports the estimations based on sub-advised active equity funds. *AT* is air traffic as defined in (1). *Fund Flow* is estimated fund flow as defined in (11). *Raw Return* and *Excess Return* are fund 12-month raw return and fund 12-month excess return, respectively. Alpha^{CAPM} , Alpha^{FF-3} , and $\text{Alpha}^{4-Factor}$ are one-year CAPM alpha, one-year Fama-French three-factor (FF-3) alpha, and one-year Carhart four-factor (4-Factor) alpha, respectively. The variables are winsorized at 1%, and the standard errors are clustered at the fund level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A. Full Sample

	(1)	(2)
	Advisory Fee	Advisory Fee
AT_{t-1}	-0.001** [-2.208]	-0.001** [-2.208]
$Fund\ Flow_{t-1}$	-0.000 [-0.206]	-0.000 [-0.207]
$Raw\ Return_{t-1}$	-0.009 [-0.703]	
$Excess\ Return_{t-1}$		-0.008 [-0.674]
Year FE	Yes	Yes
Fund FE	Yes	Yes
Subadv FE	Yes	Yes
R-squared	0.97	0.97
#Obs. F-S-Year	10,055	10,055

Panel B: Sample of Active Equity Funds

	(1) Advisory Fee	(2) Advisory Fee	(3) Advisory Fee	(4) Advisory Fee	(5) Advisory Fee
AT_{t-1}	-0.001** [-2.409]	-0.001** [-2.410]	-0.001** [-2.420]	-0.001** [-2.423]	-0.001** [-2.423]
$Fund\ Flow_{t-1}$	-0.000 [-0.128]	-0.000 [-0.129]	-0.000 [-0.134]	-0.000 [-0.143]	-0.000 [-0.132]
$Raw\ Return_{t-1}$	-0.006 [-0.290]				
$Excess\ Return_{t-1}$		-0.005 [-0.268]			
$Alpha_{t-1}^{CAPM}$			0.141 [0.761]		
$Alpha_{t-1}^{FF-3}$				0.341* [1.954]	
$Alpha_{t-1}^{4-Factor}$					0.292* [1.833]
Year FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Subadv FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.963	0.963	0.963	0.964	0.963
#Obs. F-S-Year	8,034	8,034	8,034	8,034	8,034

Table 9: Management Outsourcing with High Information Asymmetry

Table 9 exhibits the results of the tests on how information asymmetry affects air traffic's (AT's) influence on fund management outsourcing. The dependent variables in Panel A are the number of new management subcontracts for active equity (AEQ) funds and non-active-equity (NAEQ) funds, and the ratio of new subcontracts for AEQ funds and equity (EQ) funds over total new subcontracts. The dependent variables in Panel B are performance improvement of NAEQ funds and actively managed NAEQ funds. Fund performance is measured as raw returns and excess returns. The dependent variable in Panel C is the advisory fees of NAEQ funds and actively managed NAEQ funds. The variables are winsorized at 1%. The standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Subcontracting Events

	(1)	(2)	(3)	(4)
	N (New AEQ-Fund-Level Relations)	N (New NAEQ-Fund-Level Relations)	New AEQ Funds Subcontracting Ratio	New EQ Funds Subcontracting Ratio
AT_{t-1}	0.002** [2.200]	0.001** [2.320]	0.001** [2.152]	0.001** [2.135]
FundMMSA*Year FE	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes
R-squared	0.61	0.621	0.359	0.362
#Obs. F-S-MMSA- Year	26,341	26,341	52,033	52,033

Panel B: Performance Improvement for NAEQ Funds with New Subcontracts

	NAEQ Funds		Active NAEQ Funds	
	(1)	(2)	(3)	(4)
	Raw Return	Excess Return	Raw Return	Excess Return
AT_{t-1}	-0.081 [-0.335]	-0.194 [-0.719]	-0.050 [-0.199]	-0.169 [-0.610]
$Fund\ Size_t$	0.004 [0.792]	0.004 [0.787]	0.005 [0.833]	0.005 [0.826]
$Mgmt.\ Fee_t$	-0.032 [-1.262]	-0.035 [-1.321]	-0.031 [-1.086]	-0.035 [-1.132]
$Turnover_t$	-0.001 [-0.208]	-0.002 [-0.246]	-0.001 [-0.327]	-0.002 [-0.360]
FundMMSA*Year FE	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes
R-squared	0.885	0.887	0.895	0.897
#Obs. Subcontracting Events	355	355	292	292

Panel C: Advisory Fees for NAEQ Funds

	(1)	(2)
	Advisory Fee for NAEQ Funds	Advisory Fee for Non-Equity Active Funds
AT_{t-1}	0.000 [0.500]	-0.000 [-0.363]
$Fund\ Flow_{t-1}$	-0.002 [-1.430]	-0.003** [-2.049]
$Raw\ Return_{t-1}$	-0.006 [-0.893]	
$Excess\ Return_{t-1}$		-0.004 [-0.342]
Year FE	Yes	Yes
Fund FE	Yes	Yes
Subadv FE	Yes	Yes
R-squared	0.990	0.989
#Obs. F-S-Year	1,989	1,557

Table 10: Introduction of New Flights

Table 10 exhibits the results of the regression identified in (12), (13), and (14). Panel A reports the estimates of the specification (12), and the dependent variables are the number of new management subcontracts for all funds and active equity (AEQ) funds. The independent variable, Treatment, is the $[1, 3]$ event window dummy as defined in (12). Panel B shows the results of the parallel trend test. The independent variables include the indicators of each year in the $[-3, 3]$ event window around the introduction of new flights. The dependent variables in Panel C and Panel D are fund returns in the current year, including 12-month raw returns, 12-month excess returns, one-year CAPM alphas, one-year Fama-French three-factor (FF-3) alphas, and one-year Carhart four-factor (FF-4) alphas. The return measures in Panel D are in percentage numbers. The independent variable in Panel C and Panel D, Treatment, is the indicator of the treated fund-subadvisor city pair being in the first year after the introduction of new flights. Panel C displays the results of the specification (13). Panel D displays the results of the specification (14). $Alpha_{CAPM, t-1}^-$ and $Alpha_{CAPM, t-1}^+$ denote past 12-month CAPM negative alphas and non-negative alphas, respectively, as defined in (14). The variables are winsorized at 1%, and the standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Treatment Effect

	(1)	(2)
	N (New Fund-Level Relations)	N (New AEQ-Fund-Level Relations)
<i>Treatment</i> [+1, +3]	0.048** [2.295]	0.029** [2.420]
FundMMSA*Year FE	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes
F-S MMSA Pair FE	Yes	Yes
R-squared	0.473	0.362
#Obs. F-S-MMSA-year	52,033	52,033

Panel B: Parallel Pre-Trend

	(1)	(2)	(3)	(4)
	N (New Fund-Level Relations)	N (New Fund-Level Relations)	N (New AEQ-Fund- Level Relations)	N (New AEQ-Fund-Level Relations)
<i>Treatment</i> [−3]	-0.011 [-0.410]	-0.011 [-0.411]	0.015 [1.188]	0.015 [1.187]
<i>Treatment</i> [−2]	-0.006 [-0.277]	-0.006 [-0.277]	0.011 [0.811]	0.011 [0.811]
<i>Treatment</i> [−1]	-0.034* [-1.897]	-0.034* [-1.900]	0.004 [0.421]	0.004 [0.420]
<i>Treatment</i> [0]	0.034 [1.310]	0.034 [1.314]	0.019 [1.417]	0.019 [1.422]
<i>Treatment</i> [+1]	0.040 [1.367]		0.034** [2.119]	
<i>Treatment</i> [+2]	0.054* [1.786]		0.034** [2.069]	
<i>Treatment</i> [+3]	0.054 [1.438]		0.043** [2.246]	
<i>Treatment</i> [+1, +3]		0.047* [1.902]		0.036*** [2.811]
FundMMSA*Year FE	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes
R-squared	0.473	0.473	0.362	0.362
#Obs. F-S-MMSA-year	52,033	52,033	52,033	52,033

Panel C: Performance of Funds with New Subcontracting

	(1) Raw Return	(2) Excess Return	(3) CAPM Alpha	(4) FF-3 Alpha	(5) 4-Factor Alpha
<i>Treatment</i> [+1]	0.085*** [3.287]	0.086*** [3.312]	0.019*** [7.788]	0.025*** [6.199]	0.029*** [14.232]
<i>Fund Size_t</i>	0.000 [0.002]	-0.000 [-0.011]	-0.000 [-0.323]	-0.000 [-0.457]	-0.000 [-0.768]
<i>Mgmt. Fee_t</i>	-0.011 [-0.860]	-0.011 [-0.862]	-0.001 [-1.276]	-0.001 [-0.739]	-0.000 [-0.449]
<i>Turnover_t</i>	-0.008 [-0.968]	-0.008 [-0.966]	0.000 [0.737]	0.000 [0.294]	-0.000 [-0.134]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.900	0.902	0.464	0.517	0.504
#Obs. FS Relations	1,458	1,458	1,458	1,458	1,458

Panel D: Performance of Existing Subcontracts

	(1) Raw Return	(2) Excess Return	(3) CAPM Alpha	(4) FF-3 Alpha	(5) 4-Factor Alpha
<i>Treatment</i> [+1]	-1.008 [-0.518]	-1.004 [-0.517]	-0.084 [-0.421]	-0.105 [-0.756]	-0.149 [-1.163]
<i>Alpha</i> _{CAPM, t-1} ⁻	-0.325 [-0.547]	-0.317 [-0.535]	-0.030 [-0.751]	0.091*** [2.686]	0.041 [1.251]
<i>Treatment</i> [+1] * <i>Alpha</i> _{CAPM, t-1} ⁻	-7.243*** [-2.933]	-7.247*** [-2.941]	-0.569** [-2.384]	-0.579*** [-3.435]	-0.653*** [-3.610]
<i>Alpha</i> _{CAPM, t-1} ⁺	-3.315*** [-6.541]	-3.291*** [-6.524]	-0.304*** [-6.639]	-0.185*** [-5.473]	-0.174*** [-4.508]
<i>Treatment</i> [+1] * <i>Alpha</i> _{CAPM, t-1} ⁺	15.579*** [2.666]	15.555*** [2.664]	1.276*** [2.911]	0.792* [1.966]	0.840** [2.251]
<i>Fund Size</i> _t	0.117 [1.262]	0.117 [1.262]	0.003 [0.446]	-0.010 [-1.473]	-0.012 [-1.628]
<i>Mgmt. Fee</i> _t	-1.270** [-2.544]	-1.269** [-2.550]	-0.072* [-1.768]	-0.079** [-2.105]	-0.107*** [-2.722]
<i>Turnover</i> _t	-1.120*** [-4.108]	-1.117*** [-4.117]	-0.016 [-0.682]	-0.021 [-0.953]	-0.015 [-0.652]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes
FS-MMSA pair FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.813	0.816	0.348	0.360	0.367
#Obs. FS Relations	5,934	5,934	5,934	5,934	5,934

Table 11. The 2004 DFW Airport Hub Closure by Delta Airlines

Table 11 exhibits the results of the regression identified in (12). The dependent variables are the number of new management subcontracts at the firm level and at the fund level. The independent variables include the indicators of each year in the $[-3, 3]$ event window around the closing of the DFW airport hub by Delta in 2004. The sample period is from 2001 to 2007 and the subcontract sample is from N-SAR B filings. The variables are winsorized at 1%, and the standard errors are clustered at the Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

	(1) N (New Firm- Level Relations)	(2) N (New Firm- Level Relations)	(3) N (New Firm- Level Relations)	(4) N (New Fund- Level Relations)	(5) N (New Fund- Level Relations)	(6) N (New Fund- Level Relations)
<i>Treatment</i> [+1, +3]	-0.105* [-1.790]		-0.074* [-1.908]	-0.119** [-2.157]		-0.096* [-1.898]
<i>Treatment</i> [-2]		0.139 [0.943]	0.139 [0.943]		0.119 [0.778]	0.119 [0.778]
<i>Treatment</i> [-1]		0.009 [0.291]	0.009 [0.291]		0.022 [0.390]	0.022 [0.390]
<i>Treatment</i> [0]		-0.032 [-0.867]	-0.033 [-0.897]		-0.058 [-0.989]	-0.059 [-0.996]
<i>Treatment</i> [+1]		-0.079 [-1.567]			-0.121* [-1.775]	
<i>Treatment</i> [+2]		-0.096** [-2.469]			-0.109* [-1.846]	
<i>Treatment</i> [+3]		-0.036 [-0.780]			-0.050 [-0.897]	
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FSMMSA_Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.429	0.429	0.429	0.537	0.537	0.537
#Obs. FS Relations	27,413	27,413	27,413	27,413	27,413	27,413

Table 12: Placebo Tests

Table 12 exhibits the results of the regression specified in (4) using the three alternative identifications of Fund-Subadvisor Metro/Micropolitan Statistical Area (F-S MMSA) pairs and corresponding identifications of AT. New subcontracts are counted as numbers at the firm level and fund level. Branch-Headquarter F-S MMSA pairs are fund company branch–subadvisor headquarter MMSA pairs with the shortest geographical distances. Headquarter-Branch F-S MMSA pairs are investment company headquarter–subadvisor branch MMSA pairs with the shortest geographical distances. NR F-S MMSA pairs are F-S MMSA pairs reported in N-SAR B filings. The variables are winsorized at 1%, and the standard errors are clustered at the F-S MMSA pair level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

	BH F-S MMSA pairs		HB F-S MMSA pairs		NR F-S MMSA pairs	
	(1)	(2)	(3)	(4)	(5)	(6)
	N (New Firm- Level Relations)	N (New Fund- Level Relation)	N (New Firm- Level Relations)	N (New Fund- Level Relation)	N (New Firm- Level Relations)	N (New Fund- Level Relation)
AT_{t-1}	0.0001	0.0003	0.0002	0.0000	0.0002	0.0008
	[0.266]	[0.381]	[0.395]	[-0.002]	[1.020]	[1.086]
FundMMSA*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SubadvMMSA*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-S MMSA Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.358	0.466	0.362	0.486	0.296	0.416
#Obs. F-S-MMSA-Year	49,555	49,555	40,640	40,640	61,505	61,505

Table 13: Determinants of Management Outsourcing and Subadvisor Turnover

Table 13 exhibits the results of the tests about how information cost reductions affect fund-side performance. The regressions are at the fund-year level. Panel A shows the determinants of distant sub-advising activities (DSA) by event types, as specified in (15). All three types of subcontracting events—“Enter” (first-time subcontracting), “Replace” (adding at least one new subadvisor while dropping at least one existent subadvisor), and “Add” (adding at least one new subadvisor without dropping any existent subadvisor)—are studied. The first column reports full sample results. Column (2) to column (4) report subsample test results based on different DSA event types. Column (5) reports results for all DSA events with interaction items as explanatory variables. Column (6) repeats the test of column (5) with the sample of sub-advised funds only. $I(Enter)$, $I(Replace)$, and $I(Add)$ are dummy variables for the event type of “Replace,” “Add,” and “Enter,” respectively. Panel B shows results on how the aggregated departing air traffic (ADAT) affects funds’ subadvisor turnover decisions, as specified in (16). $ADAT$ is the aggregated departing air traffic as defined in (2). $Alpha^{FF-3}$ is the one-year Fama-French three-factor (FF-3) alpha. $Fund\ Size$ is the log of CRSP fund total net assets. $Fund\ Size\ Growth$ is the yearly growth of CRSP fund total net assets. The variables are winsorized at 1%, and the standard errors are clustered at the fund level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A: Determinants of Distant Sub-Advising Activities by Event Types

	(1) DSA	(2) Enter	(3) Replace	(4) Add	(5) DSA	(6) DSA
$ADAT_{t-1}$	0.010** [2.441]	0.009** [2.548]	0.001 [0.400]	0.000 [0.621]	-0.000 [-0.181]	-0.019 [-0.971]
$Alpha_{t-1}^{FF-3}$	-0.983*** [-4.847]	-0.293** [-2.565]	-0.640*** [-4.085]	-0.050 [-0.883]	-0.389*** [-3.775]	-1.253*** [-3.742]
$Fund\ Size_t$	0.004*** [3.996]	-0.000 [-0.907]	0.003*** [4.245]	0.001*** [4.272]	0.001* [1.921]	0.000 [0.254]
$ADAT_{t-1} * I(Enter)$					0.256*** [29.166]	
$ADAT_{t-1} * I(Replace)$					0.241*** [29.446]	0.238*** [29.498]
$ADAT_{t-1} * I(Add)$					0.236*** [15.453]	0.234*** [15.906]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FundMSA FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.030	0.029	0.028	0.006	0.689	0.712
#Obs. Fund-Year	23,586	23,586	23,586	23,586	23,586	5,593

Panel B: Subadvisor Turnover

	(1) Turnover	(2) Turnover	(3) Turnover	(4) Turnover	(5) Turnover
$ADAT_{t-1}$	-0.003*** [-3.552]	-0.002*** [-3.299]	-0.003*** [-3.367]	-0.002** [-2.305]	-0.003** [-2.547]
$Alpha_{t-1}^{FF-3}$		-1.726** [-2.525]		-1.881** [-2.441]	
$ADAT_{t-1} * Alpha_{t-1}^{FF-3}$		0.085 [0.890]		0.143 [1.274]	
$Fund\ Size\ Growth_{t-1}$			-0.004 [-0.852]		-0.008 [-1.419]
$ADAT_{t-1} * Fund\ Size\ Growth_{t-1}$			-0.000 [-0.248]		-0.000 [-0.254]
$Fund\ Size_t$				-0.004 [-1.633]	-0.006** [-1.971]
$Mgmt.\ Fee_t$				-0.008 [-0.595]	-0.018 [-1.235]
$Turnover_t$				0.034*** [3.695]	0.033*** [3.245]
Year FE	Yes	Yes	Yes	Yes	Yes
FundMSA FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.031	0.032	0.036	0.054	0.061
#Obs. Fund-Year	11,729	11,729	10,011	7,409	6,577

Table 14: Air Traffic and Delegated Asset Management Business of Subadvisors

Table 14 exhibits the relation between subadvisor-level air traffic and the delegated asset management business from fund companies. The subadvisor year-level regression is specified in (17). The first four columns report the results using the log number of investment firms (CIK) that have assets delegated to a subadvisor's management as the measure of the size of outsourcing business, and the dependent variable in the last four columns is the log number of mutual funds under a subadvisor's management. $AAAT$ is the aggregated arriving air traffic as defined in (3). $Advisor\ Size$ is the log number of the total assets under subadvisors' discretionary management from ADV filings. $Alpha^{FF-3}$ is the value-weighted one-year Fama-French three-factor (FF-3) alpha of equity funds managed by advisory firms. $Experience$ is the number of years an advisory firm has worked as a subadvisor. If an advisory firm worked as a subadvisor in 1996 when the NSAR-B files started to become available, the beginning year for computing its experience is set as 1996. The variables are winsorized at 1%, and the standard errors are clustered at the subadvisor level. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LogN(Firm)	LogN(Firm)	LogN(Firm)	LogN(Firm)	LogN(Fund)	LogN(Fund)	LogN(Fund)	LogN(Fund)
$AAAT_{t-1}$	0.009 [0.252]	-0.012 [-0.233]	0.347*** [2.655]	0.345** [2.360]	0.013 [0.326]	-0.003 [-0.050]	0.352* [1.893]	0.353** [2.026]
$Advisor\ Size_{t-1}$		0.160*** [3.851]	0.440*** [4.747]	0.432*** [3.692]		0.192*** [3.410]	0.469*** [3.826]	0.459*** [3.691]
$Alpha_{t-1}^{FF-3}$		0.133 [0.085]	0.213 [0.135]	11.924* [1.866]		0.787 [0.492]	0.867 [0.537]	19.819*** [2.996]
$Experience_t$		0.015 [1.023]	0.014 [0.929]	0.029 [0.748]		0.011 [0.378]	0.010 [0.332]	0.034 [0.679]
$AAAT_{t-1}$ * $Advisor\ Size_{t-1}$			-0.016*** [-2.748]	-0.016** [-2.189]			-0.016* [-1.946]	-0.016* [-1.838]
$AAAT_{t-1} * Alpha_{t-1}^{FF-3}$				-0.715* [-1.817]				-1.156*** [-2.897]
$AAAT_{t-1} * Experience_t$				-0.001 [-0.456]				-0.002 [-0.620]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubAdvMSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubAdv FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.867	0.900	0.901	0.901	0.862	0.893	0.894	0.895
#Obs. Subadvisor-Year	2,605	1,634	1,634	1,634	2,605	1,634	1,634	1,634