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Are Some Clients More Equal Than Others? An Analysis of Asset Management Companies' Execution Costs*

Azi Ben-Rephael[1] and Ryan D. Israelsen[2]

[1]Kelley School of Business, Indiana University and [2]Broad College of Business, Michigan State University

Abstract

Previous research documents differences in trading desk skills across management companies that result in significant variation in execution costs. In this paper, we utilize links between management companies and their institutional clients to explore variation in execution costs within management companies. For a subset of management companies, we find that systematic differences in execution costs exist across clients; these differences are comparable to the variation documented across management companies and persist over time. Clients who receive lower execution costs reward management companies with an increase in dollar trading volume. We find no evidence that the results are driven by broker commissions or differences in trading practices. Given the economic significance of our findings and implications for institutional investors, this aspect of execution should be recognized regardless of the ultimate source of the differences.

JEL classification: G11, G20, G23

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1. Introduction

Institutional investors trade billions of dollars' worth of securities each day, and trading costs are economically significant to portfolio managers and their clients.[1,2] As a result, management companies have strong incentives to minimize trading costs. To do so, they engage in multiple strategies, including splitting order flows to reduce the price impact of trades (e.g., Chakravarty, 2001; Alexander and Peterson, 2007). However, managing trading costs requires effort and, given the intense competition across market participants and constant variation in market conditions, this effort is not trivial.

Anand *et al.* (2012) study differences in trading desk skills across management companies and find large, economically significant variation in execution costs. In addition to such differences between management companies, the allocation of limited resources across clients may lead to significant variation within a single management company's execution costs, even when its average execution costs are low. In this paper, we examine whether such variation exists, and, if so, what factors may explain it.

As part of their daily trading activity, management companies routinely buy or sell the same stocks for multiple clients on the same day (also called bunching or "bunched trades"). This is a natural result of sharing similar information and managing correlated portfolios across clients (see, e.g., Elton, Gruber, and Green, 2007).

Consider the following example: a management company decides to buy 20,000 shares of stock XYZ for each of its five institutional clients—a total of 100,000 shares. The execution is the responsibility of the management company's trading desk. Naturally, if the trade is large or if prices are volatile, the overall bunched trade may be executed via multiple trades at different prices. Suppose that the execution costs across these trades vary between 10 and 50 basis points. The management company then needs to decide how to allocate the trades and will instruct the back office accordingly.

Based on ADV filing statements, it is clear that management companies decide on a particular order of execution every time they execute trades for a given stock across clients.[3] The order may be random, rotated by some arbitrary rule, or based on time-varying client needs. While management companies often mention that client trades may be prioritized

1 In 2015, the daily global dollar trading volume of equities was about $500 billion (see https://www.world-exchanges.org/home/index.php/news/world-exchange-news/wfe-full-year-statistics-show-2015-global-equity-trading-volumes-rise-55-as-volatility-boosts-activity).

2 For studies on direct trading costs see Amihud and Mendelson (1986), Stoll (2000), Amihud (2002), and Bessembinder (2003). For general execution trading cost measures see Perold (1988); Berkowitz, Logue, and Noser (1988); Madhavan (2002); and Hu (2009). For studies on trading costs using trading data see Chan and Lakonishok (1995); Keim and Madhavan (1997); Jones and Lipson (2001); Chiyachantana *et al.* (2004); Goldstein *et al.* (2009); and Anand *et al.* (2012, 2013).

3 Form ADV is the uniform form used by investment advisers to register with both the Securities and Exchange Commission and state securities authorities. The form consists of two parts. Part 1 requires information about the investment adviser's business, ownership, clients, employees, business practices, affiliations, and any disciplinary events of the adviser or its employees. Part 2 requires investment advisers to prepare narrative brochures written in plain English that contain information such as the types of advisory services offered, the adviser's fee schedule, disciplinary information, conflicts of interest, and the educational and business background of management and key advisory personnel of the adviser. For more information please look at https://www.sec.gov/fast-answers/answersformadvhtm.html.

differently, it is not clear why differences in priority should lead to systematic differences in execution costs across all trades over time.[4] This raises the possibility that such systematic differences may be a result of management companies intentionally favoring a subset of clients. In particular, a growing body of literature on conflicts of interest provides compelling evidence of favoritism in the management company industry (see Gaspar, Massa, and Matos, 2006; Chaudhuri, Ivković, and Trzcinka, 2017, among others).[5]

We seek to establish whether systematic variation in trading costs across clients exists or whether any cost differences are purely random. Thus, our null hypothesis is defined as follows: (H0)—"there are no systematic differences in execution costs across clients within a management company." If the null hypothesis is rejected, we hypothesize that systematic differences could result from two possible mechanisms: (H1a)—"systematic differences across clients are due to the intentional allocation of execution costs" or (H1b)—"systematic differences across clients are an unintended consequence of general differences in trading practices."

We use the same ANcerno database of institutional trades that is used in Anand *et al.* (2012, 2013) (hereafter, AIPV), with one important distinction: ANcerno provided us with identification codes that enable us to link institutional clients to their management companies. These links are crucial to our study since they allow us to track the trades made by a management company for its institutional clients.

ANcerno's institutional clients are primarily mutual funds (which are aggregated at the family level) and pension plan sponsors. We focus on pension plan sponsors which are ideal for our analysis since it is common in the pension plan industry for management companies to manage multiple portfolios across different plan sponsors. Moreover, the pension plan industry is economically important, with around $7 trillion dollars of assets under management.[6,7]

To examine differences in execution costs, we use the execution shortfall measure (ESF), which compares the execution price with the open price benchmark. As in AIPV (2012, 2013), we account for the effect of stock characteristics on ESF, and use the residual of ESF

4 Two examples from the ADV filings are: (1) "it is not unusual to have multiple aggregated orders and differing priorities for the same security at the same time. In such cases, certain client accounts may get a higher or lower price for the same security than orders for other clients."; (2) ". . . may determine in its sole discretion to place transactions for one group of accounts before or after the remaining accounts based on a variety of factors, including size of overall trade, allocation to the primary strategy, the broker dealer's commitment of capital, liquidity or other conditions of the market, or confidentiality."

5 See for example, Chalmers, Edelen, and Kadlec (2001); Gaspar, Massa, and Matos (2006); Bhattacharya, Lee, and Pool (2013); Christoffersen, Evans, and Musto (2013); Pool, Sialm, and Stefanescu (2016); and Battalio, Corwin, and Jennings (2016). Most relevant for our study, Chaudhuri, Ivković, and Trzcinka (2017) examine cross-subsidization among US equity products managed by institutional asset management firms. They find returns-based evidence consistent with both cross-subsidization receipt by strong recent performers that are relatively small in their firms and provision by products that are relatively large in their firms.

6 For more information on competition and potential conflicts of interest at the institutional asset management firms see Chaudhuri, Ivković, and Trzcinka (2017).

7 Note that, in the linking files we received from ANcerno, mutual funds are aggregated at the family level. Thus, we are not able to analyze differences in execution across individual mutual funds (e.g., Gaspar, Massa, and Matos, 2006).

(denoted as ResESF) from monthly cross-sectional regressions of clients' ESF on clients' trading volume and various stock characteristics. Moreover, given our motivation, we explore the decisions made by management companies when executing trades across multiple clients. Consequently, we focus on what we define as shared trades, which are trades made by a management company for more than one institutional client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different execution prices, that are executed by the same brokerage firm. Notably, this structure allows us to eliminate potential conflicting explanations such as trading desk skills, liquidity trading style, and stock-picking abilities that may confound our estimates.

We begin with in-sample tests to exploring H0. In particular, we rank clients within management companies based on their ResESF averages and test whether differences in averages between the top-ranked (high execution costs) and bottom-ranked (low execution costs) clients are statistically significant. In order to control for the non-normality of this distribution, we calculate the significance levels using a simulated random execution benchmark.[8] We find that the number of management companies with statistically significant differences is between two and three times the number expected under a random execution benchmark. Thus, differences in execution costs occur in a non-negligible number of management companies. We refer to this set of management companies as the "significant management companies" group.

Next, we perform out-of-sample tests using 12-month rolling windows. We define the significant management companies within each window, and explore their subsequent out-of-sample properties. Strikingly, we find strong evidence of out-of-sample persistence in execution costs for the significant management companies group and no evidence of persistence for the non-significant group. We apply parametric and non-parametric tests including portfolio ranking and cross-sectional Fama–MacBeth regressions and find that the results are robust in each case.

To put the magnitude of ResESF into perspective, AIPV (2012) find out-of-sample differences of 60 basis points between top- and bottom-quintile ranked institutions. We find that the out-of-sample differences between top- and bottom-ranked clients can reach 60–90 basis points. Thus, the variation in trading costs within management companies is economically important.[9,10]

Having established that differences in execution costs are systematic for a significant subset of management companies, we turn to our two alternative hypotheses, H1a and H1b. We start with the relation between differences in execution costs and client dollar trading volume. Management companies may have an incentive to favor specific clients if they expect to be rewarded with higher trading volume in the future. We focus on the relation between a client's ResESF during a given 12-month window and the percentage change in dollar trading volume during the subsequent 12 months.

8 We simulate 10,000 random samples by randomly reshuffling the clients in each Management Company-Day-Stock-Broker shared trade to create the random execution null benchmark. This benchmark accounts for the type of management companies, stock characteristics, client structure, and time period in our sample. See Section 3.1 for more details.

9 It is important to note that, according to ANcerno, when it provides clients with estimates of their execution costs, it does not compare them with the costs of other clients at the same management company. Thus, it would be very difficult for ANcerno's clients to directly observe differences in execution prices.

10 Chordia, Roll, and Subrahmanyam (2011) identify a sharp uptrend in trading activity during our sample period, which suggests that these magnitudes are not negligible.

Our results indicate that for the significant management companies (as defined within the rolling window), clients with relatively low execution costs increase their trading volume by 13% over the following year. Crucially, we do not find a corresponding decline in trading volume from clients with relatively high execution costs, suggesting that management companies are able to benefit by favoring specific clients. In sharp contrast, we do not find any significant change in future trading volume in the non-significant management group.

Importantly, splitting the dollar trading volume into buy and sell dollar trading volume, we find that the 13% increase in dollar trading volume by low execution cost clients is driven by a 19.5% increase in buys and 7.3% increase in sells, thus reflecting a net positive growth in assets under management.

The evidence that management companies benefit from clients with low execution costs is consistent with H1a; however, it is also possible that clients whose execution costs are lower as an unintended consequence of general trading practices also happen to increase their future trading volume. Thus, we conduct two additional tests to show that general trading practices are unlikely to be the source of differences in execution costs across clients.[11]

In the first set of tests, we examine whether differences in clients' execution costs are specific to one management company or if they can be observed in the client's trades across other management companies. The latter would suggest that differences stem from clients' general trading needs across management companies, while the former would be more consistent with execution cost allocation within a management company.

We focus on the top- and bottom-ranked clients and explore their non-shared trades at the same management company as well as their trades at other management companies. We find that, among non-shared trades within the same management company, differences persist in the execution costs between high- and low-cost clients. In contrast, we find no differences in the execution costs for trades at other management companies, suggesting that differences in execution costs are unlikely to be driven by general client trading needs.

In the second set of tests, we directly explore variables which are associated with trading needs. We examine broker commissions, trade fill ratios, and intraday timing of trades, and investigate whether there are economically and statistically significant differences between top- and bottom-ranked clients. The results indicate that there are no significant differences in these trading measures between top- and bottom-ranked clients, which suggest that differences in trading practices are less likely to drive the observed differences in trading costs.

We examine the characteristics of management companies with systematic differences in execution costs across clients, as well as the characteristics of clients who are likely to receive higher or lower execution costs. Since the identities of clients and management companies are not disclosed, our variables are limited to those that we can construct using ANcerno's trading data. Using probit models where a significant management company is assigned a value of 1, we find that: (1) management companies with more clients tend to be in the significant group. This makes sense, since increasing the number of clients introduces more complexity into the allocation of effort in trade execution, allowing for more natural variation in costs;

11 Consistent with opportunistic behavior at the expense of institutional clients, Di Maggio *et al.* (2017) use the same ANcerno trade-level data and show that central brokers gather information by executing informed trades, which is then leaked to their best clients. In contrast, they find that when the informed asset manager is affiliated with the broker, such imitation does not occur. They argue that an important source of alpha for fund managers is the access to better connections rather than superior skill.

(2) management companies with clients who split their trading activity across multiple management companies also tend to fall into the significant group. This may reflect the competition in the industry; (3) management companies with greater shared volume are more likely to have different execution costs across clients; and (4) most importantly, we find that management companies with better trading skills (i.e., more profitable trades) and/or lower average execution costs are more likely to exhibit systematic variation in execution costs across clients. This is consistent with the notion that a management company that is more highly skilled is in a better position to pursue its own interests vis-à-vis those of its clients.

Finally, we examine the differences between high- and low-execution cost clients. Given that these clients may be different in nature, we perform separate analyses of the high-execution cost clients (top tercile of ResESF) and low-execution cost clients (bottom tercile of ResESF) within the subset of significant management companies. We use the middle tercile as the benchmark for both groups. Analyzing the probability of having lower execution costs, we find that the number of management companies per client is an important factor. As the number of management companies grows, so does competition between them, increasing a client's probability of receiving lower execution costs. We find similar results for relative trading volume. As a client brings more volume to a management company, its probability of receiving low execution costs increases. We also find that clients with shorter trading horizons are more likely to receive low execution costs, suggesting that management companies may accommodate clients for whom these costs are more important. In contrast, the probability of having high execution costs increases monotonically with the number of management companies per client, which is consistent with an attention story. Additionally, a client with concentrated trading activity at a specific management company (and thus less able to leave) is also more likely to have high execution costs. The differences in dynamics between clients with high and low execution costs suggest that intentional behavior by the management company might be at play.

To summarize, we reveal important variation in execution costs across clients in a subset of management companies. While some of the evidence is consistent with both alternative hypotheses, intentional allocation of execution costs seems to be more consistent with our overall results. Given the economic significance of our findings and their implications for institutional investors, this aspect of execution should be taken into account by market participants regardless of the ultimate source of the differences.

The remainder of the paper is organized as follows. Section 2 describes the trading environment, data, and the ESF used in the analysis. Section 3 provides evidence of systematic differences in execution prices across clients within management companies. Section 4 explores the two hypotheses for the reasons behind these differences.

Section 5 analyzes the characteristics of management companies where systematic differences in execution costs exist, as well as the differences between clients with high and low execution costs. Section 6 concludes.

2. Trading Environment, Data, and Summary Statistics

2.1 Trading Environment and Execution Process

For several reasons, the pension plan industry is an ideal setting in which to analyze differences in execution costs across clients within the same management company. First, with more than 7 trillion dollars in assets, the pension plan industry comprises a significant part of management companies' assets under management. More importantly, although some plan sponsors manage their own pools and actively make the investment decisions for retirement plans, the majority of plan sponsors outsource the fiduciary management of the assets in the plan to one or more third parties (i.e., management companies). These separate sub-portfolios, managed by different money managers, may be tailored to suit various risk profiles. For example, some of the offered products include specialized funds such as target date funds, which adjust the weights across asset classes based on the investor horizon.

We exploit the fact that many management companies often trade similar securities for multiple clients on any given day. This is an integral part of the daily trading process. Indeed, management companies mention in their ADV filings that they find it convenient to aggregate (or share) similar trades across clients for cost savings and other reasons.[12] Allocation practices may vary across management companies, and since different clients have different needs, management companies are open about the fact that some clients may receive priority in execution.[13] While we cannot directly observe what leads to these differences in execution, we can perform various analyses that improve our understanding of what drives them.

Clients' orders are typically sent to the management company's trading desk, which then decides which brokerage firm(s) will execute the trades and contacts a sales trader at each brokerage firm specifying the total amount of shares needed on a given day. The sales trader then sends the trade request (also called a ticket or tickets) to a specific trader for execution. The trader who receives the ticket from the sales trader does not typically know the identity of the individual clients, but may know the identity of the management company. If the trade is large or if prices are volatile (as may be the case with small or illiquid stocks), the overall trade may be executed with different prices. After the trader executes the trades, the execution fills are sent to back to the management company's trading desk. The allocation of the trades to the clients' accounts (through their custodians) is usually done by the back office by the end of the trading day. It is important to note that it is the management company that decides how to allocate the trades, and instructs the back office accordingly. Moreover, portfolio managers are not involved in this process and do not observe the allocation. Only if there is a problem (which should be very rare), portfolio managers may be consulted.

2.2 ANcerno's Institutional Trading Data and Sample

We obtain institutional trading data covering the period from January 1999 to September 2011 from ANcerno Ltd. ANcerno (formerly a unit of Abel/Noser Corp.) is a widely recognized consulting firm that helps institutional investors monitor their trading costs.[14] A detailed description of the data can be found in PY and Franzoni and Plazzi (2013) (hereafter, "FP").

In addition to the data used in prior studies, ANcerno provided us with identification codes that enable us to link institutional clients to their management companies. These links are crucial to our study since we explore management companies' trades across

12 In our sample, the degree of overlap in trades between clients under the same management company is high (see Table II). For institutional investors' overlap in stock holdings, see, for example, Elton, Gruber, and Green (2007).

13 The Investment Company and Adviser Acts of 1940 specify that as long as a client is informed about trading practices, the management company has fulfilled its obligation to its client.

14 Previous studies that use ANcerno data include: Anand *et al.* (2012, 2013); Busse, Green, and Jegadeesh (2012); Chemmanur, He, and Hu (2009); Chemmanur, Hu, and Li (2013); Edelen and Kadlec (2012); Franzoni and Plazzi (2013); Gantchev and Jotikasthira (2015); Goldstein, Irvine, and Puckett (2011); Huang, Tan, and Wermers (2013); Jame (2013); and Puckett and Yan (2011).

clients. To the best of our knowledge, ANcerno has made these links available for academic research only recently and for a short period of time.[15]

Our data include a number of identification codes. Clientcode is a unique numerical code assigned to all ANcerno clients (the identity of each client is not revealed). Clienttype classifies clients as pension plan sponsors (Clienttype 1), mutual funds (Clienttype 2), or brokers (Clienttype 3—a negligible portion of ANcerno's sample) based on ANcerno's internal classification. Managercode is a unique numerical code assigned to the management company (hereafter, "management company" or "MgmtCom"). These are management companies at the 13F level. The last identification variable is *Clientmgrcode*, which ANcerno assigns randomly for technical reasons or to separate positions a client may hold with the same management company. As mentioned in FP, clients usually find it convenient ANcerno to partition their relationship with a management company into several categories when reporting to ANcerno. Our analysis does not require this variable, since we examine shared trades at the management company level.

Multiple links between institutional clients and their management companies are available for pension plans (i.e., Clienttype 1). For mutual funds, the data are at the family level, with a one-to-one link between the management company and its mutual fund family.[16] Clienttype 1 includes both public and private pension plans and defined benefit and defined contribution plans. Because we do not know the clients' identities, we cannot distinguish between these plans.

Moreover, based on our discussions with ANcerno employees about the representation of the pension plan industry in their data, we have a reason to believe that the data are representative of the structure (i.e., relations between management companies and institutional clientele) and the sample of the pension plan industry.

Our primary variables include: the date of each trade (YY/MM/DD), the stock ticker and CUSIP, the number of shares per trade, the execution price of the trade, and a Buy or Sell indicator which specifies whether a trade is a buy (1) or a sell trade (−1). In general, each observation in the database describes a trade made by a management company on behalf of its client. If more than one trade was required to complete a client's order, the data include all partial executions. Each execution is a line in the data. For our purposes, we aggregate the client's "intraday trades" at the daily level.

We match our sample to CRSP using both the stock tickers and CUSIPs. To ensure the match is made correctly, we require ANcerno's daily close-price variable to match CRSP's close-price for any given trade. We exclude from our sample management companies with missing codes that cannot be matched with clients.

Our final sample of trades that are executed by a management company across multiple clients using the same brokerage firm includes 2,011,006 Management Company-Client-Day-Stock-Broker trades.[17]

2.3 The Execution Shortfall Measure

Following Anand *et al.* (2012, 2013), we use the ESF as our measure of transaction costs. In particular, we calculate the ESF as: $[(P1(t)-P0(t))/P0(t)] * D(t)]$, where $P1(t)$ is the

15 Our analysis ends in September 2011 because ANcerno has decided to scrub the data from this point forward.

16 See Franzoni and Plazzi (2013) and Eisele, Nefedova, and Parise (2016) for further discussion.

17 Controlling for the same broker is important given the evidence found in Di Maggio *et al.* (2017).

volume-weighted execution price, $P0(t)$ is the price at the open, and $D(t)$ is the sign of the trade. As AIPV argue, the shortfall measure reflects the bid–ask spread, the market impact, and the drift in price from market open to trade execution. All are important dimensions of trading desk execution decisions.[18]

Since the shortfall measure is affected by the volume of the trade and other stock characteristics, we follow AIPV and orthogonalize the measure with respect to any deterministic characteristics using monthly cross-sectional regressions. Specifically, we regress the client's shortfall measure per trade in a given management company on the client's trading volume, the client's relative volume in a shared trade, and stock characteristics including absolute return, stock volume, 1/PRC as a proxy for liquidity (where PRC is the stock price), and quintile ranking dummies of stock size, book-to-market, and momentum, based on Daniel *et al.* (1997). We denote the residual of the ESF as ResESF.

2.4 Sample Statistics

The trades in our sample are executed via 414 different management companies on behalf of 615 different institutional clients, which translates into 4246 unique Management

Company—Institutional Client pairs (MgmtCom-Client). Since we are interested in trades that are potentially shared across clients, to be included in our sample a trade needs to be made by a management company for more than one institutional client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different execution prices, and executed by the same brokerage firm. Thus, we include only management companies with more than one institutional client.

Table II reports the sample statistics for selected variables used in our analysis. For each variable, we report the time-series average of the monthly cross-sectional statistics. For example, mean (SD) is the time-series average of the cross-sectional mean (standard deviation). As mentioned, pension plan sponsors often use multiple management companies and management companies trade on behalf of multiple institutional clients. In our sample, the average number of institutional clients per Management Company is 6.37, with a standard deviation of 5.42. The average number of management companies per client is lower, with an average of 5.55. The average number of shared transactions per month is 49.67 over an average of 21.95 different stocks.

To measure the degree of portfolio overlap between clients within the same management company, we count the number of stocks traded for each client that are also traded for at least one of the management company's other clients in the same month. We then divide that number by the total number of different stocks traded by the client (i.e., shared and non-shared). The average equally weighted (value weighted) overlap ratio is 89.19% (66.87%), which indicates that the portfolios of a given management company's clients are very similar. This is not surprising given that management companies often run similar portfolios for pension plan sponsors. Moreover, the average equally weighted (value weighted) ratio of monthly shared dollar volume to the client's monthly total dollar volume is 61.10% (37.71%). Finally, the average number of months during which one or more shared trades are executed for a MgmtCom-Client pair is 22 months. The average number of months during which any trades are executed is 34 months per MgmtCom-Client pair.

18 ANcerno intraday timestamps are not available for pension plans (clienttype 1) since ANcerno typically receives the trade-data from their custodian bank. This is in contrast to other type of clients, such as money managers, who submit their own trading data through their Order Delivery System.

Table I. Variable definitions

Variable	Definition
MgmtCom	A management company at the 13F level that is uniquely identified in ANcerno with a numerical identification code.
Client	An institutional investor that uses management companies to manage all or part of its portfolio. The client is uniquely identified in ANcerno with a numerical identification code.
MgmtCom-Client	A unique pair of a management company and an institutional client, uniquely identified in ANcerno via numerical links.
ESF	The execution shortfall measure (ESF), calculated following Anand *et al.* (2013) as $[(P1(t)-P0(t))/P0(t)] * D(t)$ where $P1(t)$ is the volume-weighted execution price, $P0(t)$ is the price at the open, and $D(t)$ is the sign of trade.
ResESF	The residual of ESF is based on a monthly cross-sectional regression of a client's trade ESF on the client's trading volume, client's relative volume in a shared trade, and stock characteristics such as absolute return, stock volume, 1/PRC as a proxy for liquidity, where PRC is the stock price, and the stock's size, book-to-market and momentum quintile ranking, based on Daniel *et al.* (1997).
Client-Per-MgmtCom	The number of clients per management company.
MgmtCom-Per-Client	The number of management companies per client.
Number-Clients-Sharing-Trade	The number of clients sharing a trade. A shared trade in our sample is defined as a trade made by the same management company, for more than one institutional client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different execution prices, and executed by the same brokerage firm.
Number-MgmtCom-Client-Trades-In-Month	The number of monthly shared transactions per MgmtCom-Client pair.
Diff-MgmtCom-Client-Stocks-Shared-In-Month	The monthly number of different stocks shared per MgmtCom-Client pair.
MgmtCom-Client-Shared-DVol	The monthly shared dollar volume per MgmtCom-Client pair.
Client-Stock-Overlap-Ratio	The monthly number of overlapping stocks traded per client with other clients within the same management company, calculated using all client trades.
Client-Stock-Overlap-Ratio-VW	Client-Stock-Overlap-Ratio value weighted by client total trading volume.

(continued)

Table I. Continued

Variable	Definition
Shared-MgmtCom-Client-Vol-to-Total-Vol	The monthly ratio of a client's shared volume to its total trading volume in a given management company.
Shared-MgmtCom-Client-Vol-to-Total-Vol-VW	Shared-MgmtCom-Client-Vol-to-Total-Vol value weighed by MgmtCom-Client total trading volume.
MgmtCom-Client-Months-with-Shared-Trades	The number of months with shared trades per MgmtCom–Client pair.
MgmtCom-Client-Months-with-All-Trades	The number of months with trades per MgmtCom–Client pair.
Number-of-Partial-Trades-By-MgmtCom-Client	The number of partial trades that were required to complete an entire trade by a management company for a given client.
Volume-Per-MgmtCom-Client-Trade	The client's average dollar volume per trade executed by a management company.
Client-Per-MgmtCom2	Client-Per-MgmtCom squared.
MgmtCom-Per-Client2	MgmtCom-Per-Client squared.
Ln-MgmtCom-Total-Dvol	The natural logarithm of a management company's dollar trading volume from all clients.
Ln-Client-Total-Dvol	The natural logarithm of a client's dollar trading volume from all management companies.
Ln-MgmtCom-Client-Shared-DVol	The natural logarithm of MgmtCom-Client-Shared-DVol
Ln-Ave-MgmtCom-Client-Shared-DVol	The natural logarithm of average MgmtCom-Client-Shared-DVol for a given management company.
StockCumDGTW_20TrdDays	The stock cumulative DGTW risk-adjusted return in the 20 days following execution.
MgmtCom-Ave-ResESF	The management company's average residual ESF (ResESF) across clients.
MgmtCom-Client-Vol-to-Total-MgmtCom-Vol	The ratio of MgmtCom–Client pair's dollar volume to MgmtCom's total dollar volume.
MgmtCom-Client-Vol-to-Total-MgmtCom-Vol2	MgmtCom-Client-Vol-to-Total-MgmtCom-Vol squared.
MgmtCom-Client-Vol-to-Total-Client-Vol	The ratio of MgmtCom–Client pair's dollar volume to Client's total dollar volume.
MgmtCom-Client-Vol-to-Total-Client-Vol	MgmtCom-Client-Vol-to-Total-Client-Vol squared.
Ave-MgmtCom-Client-Stock-Trade-Gap	The average number of trading days between two subsequent transactions made by a management company for a given stock in the client's portfolio.
Pseudo-Stock-Trade-Fill-Ratio	A pseudo fill ratio that is calculated as the ratio between day t executed share volume and total executed share volume over days t and t+1 conditional on a trade being made in the same direction over the 2 days.

(continued)

Table I. Continued

Variable	Definition
TAQ-Weighed Time Interval	Since ANcerno's intraday time stamps are not available for type 1 clients, we construct a proxy for the intraday time of each trade using TAQ prices. Specifically, for each stock and 5-min interval during regular trading hours, we calculate the minimum and maximum of TAQ's trading prices together with the interval's trading volume. Each of the 78 intervals receives a time score, where the minimum time score is 1/78 (for 9:30–9:35) and the maximum time score is 78/78 (for 3:55–4:00). We then merge our sample's trades with the calculated time score proxies. In a case of a single match (i.e., the trade's price falls within a price range of a single time interval), a trade receives a unique time score. In case of a multiple match, we keep all time scores and calculate the volume-weighted average. For example, if trade X was matched with the scores 5/78 and 20/78, and volume of 100 and 2000 shares, the average score is calculated as $[(5/78) * 100 + (20/78) * 2000)]/2100 = (19.28/78)$.

Focusing on the intraday statistics, we find that the average number of trades needed to complete a shared trade (i.e., partial trades) is 2.30, and that the average volume per trade is around $286,000. Both variables are highly skewed and winsorized at the 1% and 99% levels of their distribution.

3. Differences in Execution Costs across Clients—Economic Significance of and Persistence in ResESF

We first explore whether differences in execution cost across clients have a systematic component. In Section 3.1, we calculate differences in clients' ResESFs within management companies and examine their statistical significance. In Section 3.2, we explore the out-of-sample economic significance of and persistence in observed differences in execution costs.

3.1 Significant Differences between Clients within Management Companies—in-Sample Tests

Table III begins with an in-sample test. For each management company, we identify the top- and bottom-ranked clients based on ResESF averages. We then calculate the p-value of the difference in these averages. We present results for different frequencies and p-value cutoffs. Consider first the "2 and above" columns, which are results for MgmtCom-Client pairs with at least 2 months of data in the sample.

Exploring the differences in *ex post* execution costs between top- and bottom-ranked clients, the p-values of these tests could be biased since they assume that these differences are

Table II. Summary statistics of the sample

The table reports the time-series averages of monthly cross-sectional statistics for different variables in our shared trade sample from January 1999 to September 2011—a total of 153 months. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. Similar to Anand *et al.* (2012), most of our variables are constructed at the monthly level. Thus, for each MgmtCom–Client pair we have a monthly time series over the sample time period. The basic unit in our study is the management company–client pair. Variable definitions are reported in Table I. Base Unit and Obs are the unit and number of observations used in the calculations, respectively.

Variables	Mean	Median	SD	Base Unit	Obs.
Client-Per-MgmtCom	6.37	4.63	5.42	MgmtCom-Month	19,915
MgmtCom-Per-Client	5.55	4.45	4.15	Client-Month	29,481
Number-Clients-Sharing-Trade	3.33	2.64	2.09	MgmtCom-Client-Month	93,190
Number-MgmtCom-Client-Trades-In-Month	49.67	67.10	83.81	MgmtCom-Client-Month	93,190
Diff-MgmtCom-Client-Stocks-Shared-In-Month	21.95	13.91	28.86	MgmtCom-Client-Month	93,190
Client-Stock-Overlap-Ratio	89.19	100.00	29.90	MgmtCom-Client-Month	93,190
Client-Stock-Overlap-Ratio-VW	66.87	70.67	N/A	MgmtCom-Client-Month	93,190
Shared-MgmtCom-Client-Vol-to-Total-Vol	61.10	68.55	29.90	MgmtCom-Client-Month	93,190
Shared-MgmtCom-Client-Vol-to-Total-Vol-VW	37.71	30.82	N/A	MgmtCom-Client-Month	93,190
MgmtCom-Client-Months-with-Shared-Trades	21.95	13.00	25.74	MgmtCom-Client	4246
MgmtCom-Client-Months-with-All-Trades	34.02	21.00	33.18	MgmtCom-Client	4246
Number-of-Partial-Trades-By-MgmtCom-Client	2.30	1.00	3.54	MgmtCom-Client-Day-Stock	2,011,006
Volume-Per-MgmtCom-Client-Trade	286,400	66,620	1,151,174	MgmtCom-Client-Day-Stock	2,011,006

Table III. Management companies with significant differences in execution costs across clients—in-sample tests

The table reports the percentage of management companies with significant differences in average trading costs across their institutional clients for different *p*-value levels and client sample frequencies. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al*. (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). Specifically, to test for differences between clients within a MgmtCom, we focus on the top- and bottom-ranked clients of each management company based on their sample average ResESF. We then calculate the difference between the top and bottom averages together with the *p*-value of the difference using a standard *t*-test. Frequency is the minimum number of monthly MgmtCom-Client sample observations required for inclusion in the sample. NumMgmtCom is the total number of management companies with top- and bottom-ranked clients for the specified frequency. %-Sig-Simulated-P-Values is the percentage of significant management companies at the specified significance level based on simulated samples. Due to the fact that the top- and bottom-ranked clients are selected, we adjust the null benchmark to account for this selection. Specifically, to create a distribution under the null hypothesis of random execution, we simulate 10,000 random samples by reshuffling the clients in each MgmtCom-Day-Stock-Broker shared trade. Using the MgmtCom-Day-Stock unit accounts for the type of stock, time, and management company characteristics. For each simulated sample, we calculate the difference between the average ESF of the top- and bottom-ranked clients and the associated *p*-value of that difference and store the information. We then use each management company distribution to locate the nominal *p*-value in that distribution. % Sig MgmtCom (# Sig MgmtCom) is the percentage (number) of all management companies that are significant using the simulated *p*-values.

Frequency	2 and above			6 and above			12 and above		
P-value	10%	5%	1%	10%	5%	1%	10%	5%	1%
Num MgmtCom	387	387	387	324	324	324	262	262	262
% Sig MgmtCom	18.09%	13.44%	7.49%	20.99%	15.74%	8.95%	21.76%	16.03%	9.92%
# Sig MgmtCom	70	52	29	68	51	29	57	42	26

normally distributed. Consequently, we use a simulation-based approach to assign the appropriate *p*-values which adjust for the ranking procedure.[19] Since the analysis is conducted at the management company level, we construct 10,000 simulated samples for each of the management companies in our sample. In each simulation round, we keep the MgmtCom-Day-Stock-Broker unit and reshuffle the trading costs across the clients sharing the trade. This allows us to account for the type of stock, time in sample and general execution characteristics. Then, we rank the clients based on their simulated ResESF averages, calculate the differences in execution costs between the top- and bottom-ranked clients, and store the simulated *p*-value. After simulating 10,000 random samples for each management company, we calculate the

19 Other examples of papers using simulated benchmarks are: Kosowski *et al.* (2006) and Fama and French (2010).

significance level of each management company based on the location of the empirical p-value (i.e., the original p-value under the normal distribution) in the simulated p-value distribution.

Table III reports the percentage of management companies with significant differences in execution costs between the top- and bottom-ranked clients. The analysis clearly indicates that the number of significant cases is much higher than what would be expected by chance. Consider, for example, the 5% cutoff; there are three times more significant cases than expected under a random execution outcome. Thus, these differences in priority of execution occur in a systematic manner for a significant subset of management companies.

3.2 Significance and Magnitudes of Differences between Clients within Management Companies—Out-of-Sample Tests

Next, it is important to show that differences in execution are economically significant and persistent in nature. In Table IV, we use a set of out-of-sample tests to provide evidence on the economic magnitude of and persistence in differences in execution costs across clients. We split each client's set of trades within a specific management company into two equal sub-periods, which we denote as the Ranking period and the Post-Ranking period, respectively. Next, we calculate each client's average ResESF during both periods. Using these averages, we calculate the difference in ResESF between the top- and bottom-ranked clients for each management company in the Ranking period, as well as their associated p-values. We define the significant management companies during the Ranking period as those with p-values of less than 5%. Finally, we calculate the averages and differences in ResESF between the top- and bottom-ranked clients during the Post-Ranking period.

The results show that both groups (the significant and non-significant management companies) have relatively similar ResESF magnitudes during the Ranking period. However, the Post-Ranking period reveals stark differences between the two groups. Specification 1 provides evidence of a strong persistence in trading costs for the significant management company group, with a persistence ratio between 56% and 71%. The magnitudes of the ResESF averages in absolute terms are sizeable, ranging from 0.53% to 0.68%. In contrast, Specification 2 shows that such persistence does not exist for the non-significant management companies. In fact, there is evidence of a reversal.

Motivated by this evidence, we next explore the out-of-sample transition matrix of clients within management companies based on ResESF and the out-of-sample economic magnitude. Using rolling information from calendar months $m-12$ to $m-1$, which we denote as the Ranking window, we define significant management companies as those with differences between their top- and bottom-ranked clients with a p-value of 5% or less. To leave a clearer distinction between the two groups, non-significant management companies are defined as those with differences that have a p-value of 10% or more.[20]

In the second step, we rank clients within management companies into terciles based on their average ResESFs during the Ranking window and during the out-of-sample 12-month period from months m to $m+11$, which we define as the Post-Ranking window. Finally, we use the information from both periods to calculate the clients' ResESF transition matrix and the economic magnitudes of the out-of-sample ResESF.

Table V reports these results, where Panel A(B) explores the significant (non-significant) management companies. The results confirm Table IV's findings. Using all clients (Post-

20 Using the 5% cutoff produces qualitatively similar results.

Table IV. Management companies with significant differences in execution costs across clients—out-of-sample subsamples tests

The table reports the ResESF averages of management companies' top- and bottom-ranked clients during the Ranking and Post-Ranking periods. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). For each management company, we divide the monthly ResESF observations for each client into two equal periods. We then define the first period as the Ranking period, and the second period as the Post-Ranking period. This allows us to look at changes in each client's ResESF during the sample period. To define the significant and non-significant management companies, we rank clients within each management company by their ResESF averages during the Ranking period and keep the top-ranked (high execution costs) and bottom-ranked clients (low execution costs). We then calculate the difference in the averages and define the significant management companies as those with *p*-values that are less than 5%. To leave a clearer distinction between the two groups, the non-significant management companies are defined as those with a *p*-value of 10% or more. Next, we calculate the average ResESFs of the top-ranked and bottom-ranked clients (which are defined in the Ranking period) during their Post-Ranking period. Specification 1 (2) presents results for the significant (non-significant) management companies. Frequency is the minimum number of monthly MgmtCom-Client sample observations required for inclusion in the sample. Ranking Period is based on the first half of the clients' sample and Post-Ranking Period is based on the second half of the clients' sample for a given management company. HighExc Average is the average of the significant management companies' top-ranked clients. LowExc Average is the average of the significant management companies' bottom-ranked clients. Diff is the difference between the top- and bottom-ranked clients. Persistence Ratio High (Persistence Ratio Low) is the ratio between the top (bottom) client averages in the Post-Ranking Period and Ranking Period.

	SigMgmtCom (1)		NonSigMgmtCom (2)	
Frequency	Freq. ≥6	Freq. ≥12	Freq. ≥6	Freq. ≥12
Ranking period				
HighExc Average	0.993	0.887	1.006	0.787
LowExc Average	−1.087	−0.746	−1.048	−0.763
Post-ranking period				
HighExc average	0.557	0.564	−0.121	−0.134
t-Statistic	(4.97)	(4.44)	(−1.44)	(−1.48)
LowExc average	−0.682	−0.530	0.326	0.235
t-Statistic	(−5.18)	(−4.68)	(2.99)	(2.42)
Diff	1.239	1.094	−0.447	−0.369
t-Statistic	(6.17)	(6.08)	(−3.24)	(−2.28)
Persistence ratio high	56.1%	63.6%	−12.0%	−17.0%
Persistence ratio low	62.8%	71.0%	−31.1%	−30.9%

Table V. Persistence in differences in trading costs between clients within management companies using 12-month rolling out-of-sample tests

The table reports transition matrices for clients within management companies based on their ResESF measure. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). We use a rolling window of 12 calendar months $m-12$ to $m-1$, which we define as the Ranking window, to calculate the MgmtCom-Client ResESF averages together with the p-values of the difference in averages between the management companies' top- and bottom-ranked clients. We then define significant management companies during the Ranking-window as those with p-values of less than 5%. To make a clearer distinction between the two groups, non-significant management companies are defined as those with a p-value of 10% or more. Then, we use the Ranking window to rank clients within each management company into terciles based on their average ResESF measure and store the ranking information. Next, we re-rank clients into terciles based on their average ResESF measure during the Post-Ranking window, which we define as calendar months m to $m+11$. Finally, we use all of this information to calculate the clients' transition matrix together with the average Post-Ranking tercile score and average Post-Ranking ResESF. In each panel, Post-Rank—All-Clients refers to all clients within each tercile. Post-Rank—Top-Middle-Bottom refers to the top-ranked client in tercile 3 (high execution costs), the bottom-ranked client in tercile 1 (low execution costs), and all middle-ranked clients in tercile 2. To ensure more precise estimates we require MgmtCom–Client pairs to have available data for at least 6 months during both the Ranking and Post Ranking windows. We end up with 130 rolling windows of 24 months (i.e., pre and post) out of the 153 available months in our sample.

Panel A: Significant management companies

	Post-Ranking-window—All Clients					Post-Ranking-window—Top-Middle-Bottom				
Ranking window	1	2	3	Ave Rank	Ave SF	1	2	3	Ave Rank	Ave SF
1	52.1	30.4	17.4	1.65	−0.31	60.4	25.9	13.7	1.53	−0.45
2	25.5	45.5	29.1	2.04	0.02	26.0	45.8	28.2	2.02	0.00
3	15.4	34.1	50.5	2.35	0.33	12.3	29.4	58.3	2.46	0.42
Diff.				0.70	0.64				0.93	0.87

Panel B: Non-significant management companies

	Post-Ranking-window—All Clients					Post-Ranking-window—Top-Middle-Bottom				
Ranking window	1	2	3	Ave Rank	Ave SF	1	2	3	Ave Rank	Ave SF
1	33.7	33.6	32.7	1.99	0.02	34.0	34.3	31.8	1.98	0.02
2	27.0	43.2	29.8	2.03	0.04	27.0	43.9	29.1	2.02	0.04
3	30.6	35.3	34.1	2.03	0.05	30.6	34.8	34.6	2.04	0.04
Diff.				0.04	0.03				0.06	0.02

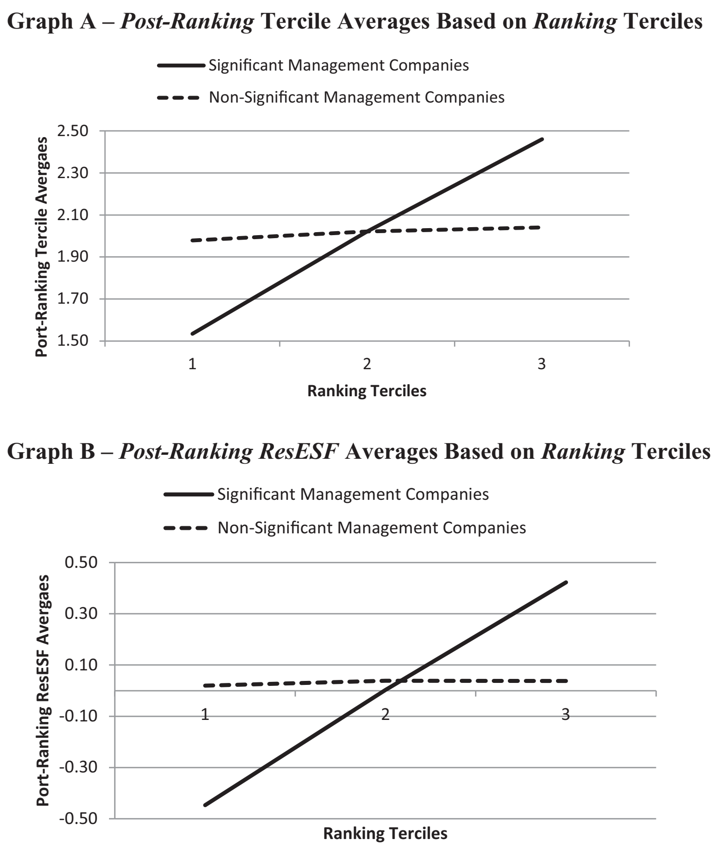

Figure 1. Out-of-sample persistence in execution costs.
Notes: The figure depicts the results reported in Table V for top-, middle-, and bottom-ranked clients. Graph **A** plots the Post-Ranking tercile averages. Graph **B** plots the Post-Ranking ResESF averages.

Ranking-window—All-Clients), we find that the probability of staying in tercile 1 (3) is 52.1% (50.5%) for a significant management company. In contrast, these probabilities for a non-significant management company are around 33–34%. Following Table IV, in our second specification we only keep the top-ranked client in Tercile 3 (high execution costs), the bottom-ranked client in Tercile 1 (low execution costs), and all middle-ranked clients in Tercile 2. Repeating the calculations for these top-, bottom-, and middle-ranked clients (Post-Ranking-window—Top-Middle-Bottom), we find that the probability of staying in the same tercile rank increases to 58–60% in the significant management company group. In contrast, the probability for the non-significant management companies is around 34%.

The economic magnitude of the out-of-sample transaction costs is also consistent with the results in Table IV. Focusing on the significant management companies, ResESF magnitudes range from −0.31% to 0.33% (−0.45% to 0.42%) using information from all clients (top-middle-bottom-ranked clients). In contrast, the ResESFs for clients of non-significant management companies range from 0.02% to 0.05%. The differences in patterns between the significant and nonsignificant groups can be clearly seen in Figure 1.

Finally, in a non-tabulated set of results, we estimate Fama–MacBeth cross-sectional correlations between ResESF averages during the Post-Ranking window and lagged ResESF averages during the Ranking window. The results are consistent with the observed transition matrices. The correlation is between 0.45 and 0.55 (0.07 and 0.10) for the significant (non-significant) management companies.

4. Exploring Potential Explanations for the Differences in Execution Costs across Clients

In this section, we explore potential explanations for the observed differences in execution costs across clients. In particular, we explore the following alternative hypotheses:

(H1a)—Systematic differences across clients are due to the intentional allocation of execution costs.

(H1b)—Systematic differences across clients are an unintended consequence of general differences in trading practices.

Since distinguishing between the two hypotheses is not trivial, we provide different tests to infer which hypothesis is more plausible based on what we can observe.

4.1 Benefits to Management Companies

A management company may have incentives to favor a subset of clients if it expects to receive future benefits from the favored clients. Such benefits may be direct (e.g., an increase in trading volume, which increases management fees) or indirect (e.g., the reputation of managing a star product). At the same time, a management company would like to avoid punishment by those clients who receive less favorable execution costs. Since we cannot observe indirect benefits, we test for direct evidence—namely, changes in trading volume from particular clients.

As in Table V, we use 12-month Ranking windows to define the significant and non-significant management companies and rank clients into terciles based on their average ResESF. In the second step, for each client in a given management company, we calculate the percentage change in dollar volume between the Ranking window and the subsequent 12 months.

The results are reported in Table VI. Panel A reveals a clear difference between the significant and non-significant management companies. For the former group, the difference in changes in trading volume between low- and high-execution cost terciles is 12%, with a t-statistic of 3.69, suggesting that clients with lower execution costs increase their trading volume by 12% relative to high-execution cost clients over the following year. In contrast, there is no significant difference in future trading volume between the low- and high-execution cost clients for the non-significant management companies. Differences across significant and non-significant management companies further confirm our findings. In particular, low-execution cost clients at significant management companies increase their trading volume by 9% relative to their counterparts at non-significant management companies, with a t-statistic of 2.75.

Moreover, the potential discriminatory behavior of management companies with statistically significant differences between clients' trading costs does not seem to elicit a negative response from high-execution cost clients. That is, we do not observe a decline in trading volume from clients who are in the top tercile. The cross differences analysis also confirms this: the percentage change in trading volume for high-execution cost clients is not significantly different between significant and non-significant management companies.

After establishing these differences, in Panel B of Table VI, we split the significant management companies trading volume into buy and sell dollar trading volume. Importantly, we find that the 13% increase in trading volume by low execution cost clients is driven by a 19.5% increase in buys and 7.3% increase in sells, thus reflecting a net positive growth in assets under management.

In sum, the evidence presented in Table VI supports the conjecture that management companies are rewarded by potentially favored clients and not punished by clients with high execution costs.

4.2 Testing for Differences in Trading Practices

4.2.1 Exploring other trades of top- and bottom-ranked clients

To explore whether the observed differences in trading costs are due to clients' specific needs, we examine other trades made for the top- and bottom-ranked clients from Table IV. We focus on two additional sets of trades: (1) non-shared trades made by the same management company and (2) all trades made by other management companies.

Table VII indicates that, within the same management company, there is persistence in both high- and low-cost clients' execution costs for these additional trades. The magnitudes are lower in the Ranking period, but out-of-sample magnitudes are comparable to Table IV's findings. In contrast, we do not find the same trends at other management companies. This suggests that the differences in execution costs are not driven by client characteristics/specific needs, since we do not find the same outcome at other management companies.

4.2.2 Testing for differences in other aspects of trading

We next explore whether differences in broker commissions, trade fill ratios, intraday timing of the trade might explain the observed differences in trading costs.

Broker commissions per trade are provided by ANcerno. Fill ratios are not reported in ANcerno; however, we calculate a pseudo fill ratio as the ratio between day t executed share volume and total executed share volume over days t and $t+1$ conditional on a trade being made in the same direction. Since intraday timestamps are not available for pension plan clients in ANcerno, we approximate the intraday time of trade using TAQ prices (see Table I for more details). Finally, we also calculate the cumulative return from execution to the end of the following day as another proxy for execution skills.

As in Table V, we use 12-month rolling windows to differentiate between the significant and non-significant management companies, and rank clients into terciles based on their ResESF. Then, for each client, we calculate the average of the variable of interest during the window period and explore the differences between top and bottom terciles. Thus, we explore the contemporaneous relation between execution costs and trading characteristics.

Panel A of Table VIII reports results for the significant management companies. The results indicate that there are generally no statistically significant differences between the top and bottom ResESF terciles. Broker commissions, pseudo fill ratios, and time of trade seem to be similar. The only variable that is statistically significant is the cumulative return from execution to the end of the following trading day. This is consistent with the observed

Table VI. Out-of-sample changes in trading dollar volume based on pre-ranking execution costs

Panel A of this table reports the out-of-sample percentage changes in dollar trading volume from management companies' clients for the significant and non-significant management companies. Panel B explores the breakdown between clients' buying and selling dollar trading volume for the significant and non-significant management companies. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). We use a rolling window of 12 calendar months $m-12$ to $m-1$, which we define as the Ranking window, to calculate the MgmtCom-Client ResESF averages together with the *p*-values of the difference in averages between the management companies' top- and bottom-ranked clients. We then define significant management companies during the Ranking window as those with *p*-values of less than 5%. To make a clearer distinction between the two groups, non-significant management companies are defined as those with a *p*-value of 10% or more. Then, we use the Ranking window to rank clients within each management company into terciles based on their average ResESF measure and store the ranking information. Next, for each client, we calculate the % change in dollar trading volume during the Post-Ranking window, which we define as calendar months m to $m+11$, and the dollar trading volume during the Ranking window. The calculation is based on total MgmtCom-Client trading volume (i.e., shared and non-shared trades). To prevent noise, we calculate dollar-weighted averages. In Panel A, Ranking window refers to the ranking based on ResESF during the Ranking window period. SigMgmtCom and NonSigMgmtCom refer to the significant and non-significant management companies, respectively. Diff. 1–3 refers to the difference between Tercile 1 and Tercile 3. Diff-Sig-NonSig refers to the difference between the significant and non-significant management companies. To ensure more precise estimates we require MgmtCom-Client pairs to have available data for at least 6 months during both the Ranking and Post Ranking windows. In Panel B, Buy Volume (Sell Volume) refers to the dollar trading from buy (sell) trading orders. There are 130 rolling windows of 24 months (i.e., pre and post) out of the 153 available months in our sample. We report the time-series averages. *t*-Statistics listed below the averages are adjusted for serial correlation using the Newey–West (1987) correction using 12 lags.

Panel A: Average changes in trading volume

	Post-Ranking window	Average % change in trading volume	
Ranking window	SigMgmtCom	NonSigMgmtCom	Diff-Sig-NonSig
1	13.44	4.50	8.94
	(4.88)	(2.60)	(2.75)
2	8.72	3.52	5.20
	(3.83)	(2.25)	(1.88)
3	1.44	4.09	−2.65
	(0.84)	(2.25)	(−1.06)
Diff. 1–3	11.99	0.41	11.58
	(3.69)	(0.16)	(2.82)

(continued)

Table VI. Continued

Panel B: Average changes in buy and sell trading volumes

	Post-Ranking window SigMgmtCom—Average % change in		Post-Ranking window NonSigMgmtCom—Average % change in	
Ranking window	Buy volume	Sell volume	Buy volume	Sell volume
1	19.48	7.31	6.97	1.99
	(5.67)	(2.34)	(2.64)	(1.03)
2	13.34	4.10	5.45	1.60
	(4.86)	(2.12)	(2.32)	(1.29)
3	2.11	0.76	6.49	1.64
	(1.53)	(0.29)	(2.87)	(1.18)
Diff. 1–3	17.37	6.55	0.48	0.35
	(4.69)	(1.61)	(0.14)	(0.15)

differences in execution prices found using ResESF. As for the non-significant companies, the differences for all variables are not statistically significant.

In sum, the results in Table VIII show no significant differences between the trading dimensions of clients who are ranked into the bottom or top ResESF terciles. These proxies suggest that the general trading practices of low-execution cost clients do not differ from those of high-execution cost clients.

5. Exploring the Characteristics of Management Companies and Clients with Significant Differences in Execution Costs

In our last set of tests, we explore the characteristics of significant management companies and the characteristics of clients that are ranked into the top and bottom ResESF terciles.

5.1 Characteristics of Significant Management Companies

We explore the characteristics of significant management companies using probit models. In particular, we estimate monthly cross-sectional probit models based on 12-month rolling window averages. Following Table V, for each of the 12-month rolling windows, we calculate the differences in execution costs across clients within management companies. Then, our dependent variable is set to 1 if a management company is in the significant management companies group and 0 otherwise. In order to have one cross-section per window, for each management company, we calculate the average of each of the explanatory variables of interest during the window, which leads to 17,406 MgmtCom-Month observations (i.e., one observation per Management Company per window). Finally, we estimate the cross-sectional probit models and report the time-series averages of the coefficient estimates together with their t-statistics.

Since the identities of clients and management companies are not disclosed, our variables are limited to those that we can construct using ANcerno's trading data. One

Table VII. ResESF averages of clients of significant management companies for non-shared trades and trades made by other management companies

The table repeats the calculations in Table IV for two additional sets of trades made for the same group of clients: (1) non-shared trades made by the same management company and (2) all trades made by other management companies. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). For each management company, we divide the monthly ResESF observations for each client into two equal periods. We then define the first period as the Ranking period, and the second period as the Post-Ranking period. This allows us to look at changes in each client's ResESF during the sample period. To define the significant and non-significant management companies, we rank clients within each management company by their ResESF averages during the Ranking period and keep the top-ranked (high execution costs) and bottom-ranked clients (low execution costs). We then calculate the difference in the averages and define the significant management companies as those with *p*-values that are less than 5%. To leave a clearer distinction between the two groups, the non-significant management companies are defined as those with a *p*-value of 10% or more. Next, we calculate the average ResESFs of the top-ranked and bottom-ranked clients (which are defined in the Ranking period) during their Post-Ranking period. Specification 1 (2) presents results for the non-shared trades made by the same management company (all trades made by other management companies). Frequency is the minimum number of monthly MgmtCom-Client sample observations required for inclusion in the sample. Ranking Period is based on the first half of the clients' sample and Post-Ranking Period is based on the second half of the clients' sample for a given management company. HighExc Average is the average of the significant management companies' top-ranked clients. LowExc Average is the average of the significant management companies' bottom-ranked clients. Diff is the difference between the top- and bottom-ranked clients. Persistence Ratio High (Persistence Ratio Low) is the ratio between the top (bottom) client averages in the Post-Ranking Period and Ranking Period.

	SigMgmtCom			
	Client other Trades at same MgmtCom		Client Trades at other MgmtCom	
	(1)		(2)	
Frequency	Freq. ≥6	Freq. ≥12	Freq. ≥6	Freq. ≥12
Ranking period				
HighExc average	0.475	0.497	0.073	0.039
LowExc average	−0.431	−0.424	0.028	0.048
Post-ranking period				
HighExc average	0.394	0.511	0.122	0.049
t-Statistic	(3.41)	(4.78)	(1.41)	(0.89)
LowExc average	−0.355	−0.306	0.058	0.053
t-Statistic	(−3.67)	(−3.26)	(0.58)	(0.67)
Diff.	0.749	0.817	0.064	−0.004
t-Statistic	(3.97)	(4.75)	(0.49)	(−0.08)

Table VIII. Testing for differences in broker commissions, trade fill ratio, time of execution, and alternative trading costs between top- and bottom-ranked clients

The table reports the differences in several trading characteristics for top- and bottom-ranked clients within a management company. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). As in Table V, we calculate the MgmtCom-Client ResESF averages for each management company, as well as the *p*-values of the difference in averages between the management companies' top- and bottom-ranked clients. We then define significant management companies during the Ranking window as those with *p*-values of less than 5%. To make a clearer distinction between the two groups, non-significant management companies are defined as those with a *p*-value of 10% or more. Next, we rank clients into terciles based on their average ResESF measure within each management company and calculate the averages of different trading characteristics. We focus on four specific variables: (1) Broker Commissions—the management company brokerage trading commission for each client, provided by ANcerno; (2) Trade Pseudo Fill Ratio—a pseudo fill ratio calculated as the ratio between day t executed share volume and total executed share volume over days t and $t+1$, conditional on a trade being made in the same direction; (3) intraday time of trade using TAQ prices (see Table I for more details); and (4) the cumulative return from execution to the end of the following day as another proxy for execution skills. There are 142 twelve-month rolling windows. We report the time-series averages. t-Statistics listed below the averages are adjusted for serial correlation using the Newey–West (1987) correction using 12 lags.

Panel A: Significant management companies

Groups	Sig MgmtCom			
	Broker commissions	Trade pseudo fill ratio	TAQ-weighed time interval	CumRet from Ex(t) to $t+1$
LowExc—Rank 1	0.137	84.89	37.41	0.33%
HighExc—Rank 3	0.134	84.94	37.23	0.18%
Diff.	0.002	0.053	0.183	−0.15%
t-Statistic	(0.41)	(0.20)	(1.09)	(−4.79)

Panel B: Non-significant management companies

Groups	Non-Sig MgmtCom			
	Broker commissions	Trade pseudo fill ratio	TAQ-weighed time interval	CumRet from Ex(t) to $t+1$
LowExc—Rank 1	0.128	86.01	37.59	0.22%
HighExc—Rank 3	0.129	85.99	38.13	0.21%
Diff.	−0.001	−0.015	−0.543	−0.01%
t-Statistic	(−0.23)	(−0.12)	(−3.25)	(−0.73)

dimension that we exploit is the availability of detailed links between clients and management companies. This allows us to use the number of clients per management company (Client-Per-MgmtCom) and the number of management companies per client (MgmtCom-Per-Client) as explanatory variables.

We also consider several other variables. First, we look at a client's shared dollar volume at a given management company, since more shared volume leads to more opportunities to give clients different priorities. Second, we include a measure of each management company's profitability. Following AIPV (2012), we calculate the 20-day DGTW-adjusted return for each trade made by the management company (StockCumDGTW_20TrdDays). The rationale is that a management company that has been successful in its investments (i.e., has displayed higher trading skills) is in a better position to pursue its own interests vis-à-vis those of its clients. We also consider the average execution cost (ResESF) of the management company across all trades made for clients (MgmtCom-Ave-ResESF), since management companies with more trading desk skill are likely better positioned to allocate execution costs.

Table IX reports the results. In all of our specifications, we make sure to control for the management company's total dollar trading volume from all of its clients. Specifications 1 and 2 capture the dynamics between management companies and their clients. We estimate both linear and non-linear specifications. The difference in pseudo-R^2 statistics suggests that a non-linear specification better captures the dynamics. Focusing on Specification 2, the coefficient on Client-Per-MgmtCom is positive and significant, while the coefficient on the squared variable is negative and significant. This suggests that the probability of being a significant management company increases with the number of clients, then eventually declines as the number becomes large. This makes sense since having multiple clients increases opportunities to allocate execution costs. On the other hand, management companies with many clients may have less incentive to favor any individual client. Graph A.1 of Figure 2, which plots the predicted probabilities based on Client-Per-MgmtCom, supports this interpretation.

Similar to the Client-Per-MgmtCom findings, the coefficient of MgmtCom-Per-Client is positive and significant while the squared variable coefficient is negative and significant. This suggests that the probability of being a significant management company increases with competition, as measured by the number of competing management companies. That is, a client with more management companies managing its portfolio is more attractive, which increases the attention of the management company to the client's specific needs. This probability begins to decline at some point, which reflects the fact that having too many management companies reduces the importance of the client's relation with any specific management company. Graph A.2 of Figure 2 supports this interpretation, where the probability of being a significant management company peaks at approximately four to eight management companies per client.

Finally, Specifications 3–5 indicate that management companies with greater shared volume are more likely to have different execution costs across clients. Most importantly, the coefficients on both StockCumDGTW_20TrdDays and MgmtCom-Ave-ResESF support our conjecture that management companies with stronger trading skills and/or overall execution are more likely to be in the significant management companies group.

Table IX. Characteristics of management companies with significant differences in execution costs

The table reports the characteristics of significant management companies using rolling Fama–MacBeth (1973) probit models of 12-month rolling windows. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). We follow the methodology in Table V, where the dependent variable receives the value of 1 if the management company is defined as a significant management company and 0 otherwise. Specifically, for each management company we calculate the MgmtCom-Client ResESF average during a rolling window of 12 calendar months. Next, we calculate the significance of the difference between the top- and bottom-ranked clients, and define the significant management companies as those with p-values of less than 5%. To create one cross-section per window, we calculate for each management company the window average of each of the explanatory variables of interest. We then run the cross-sectional probit models (i.e., one observation per MgmtCom per window) and report the time-series average of the model coefficients and their associated t-statistics. While the definition of significant management companies is based on the shared trade sample, some of the explanatory variables are based on the entire set of trades reported in ANcerno. In the table, the prefix Ln refers to the natural log of the explanatory variable, and the suffix 2 refers to the variable squared. For example, Ln-Ave-MgmtCom-Client-Shared-DVol is the natural log of Ave-MgmtCom-Client-Shared-DVol, and Client-Per-MgmtCom2 is Client-Per-MgmtCom squared. In addition, following AIPV (2012) we calculate a proxy for a management company trading ability as the average of the 20-day DGTW-adjusted return for each trade made by the management company (StockCumDGTW_20TrdDays). We also calculate the average execution cost (ResESF) of the management company across all trades made for clients (MgmtCom-Ave-ResESF). Pseudo-R^2 is the probit model's pseudo-R^2. SMP is the number of Management Company observations used in the regressions. The t-statistics listed below the regression coefficients are adjusted for serial correlation using the Newey–West (1987) correction using 12 lags.

Variables	(1)	(2)	(3)	(4)	(5)
Ln-MgmtCom-Total-Dvol	0.22	0.17	0.13	0.14	0.14
	(5.72)	(4.80)	(3.18)	(3.14)	(2.92)
Client-Per-MgmtCom	0.06	0.23	0.25	0.25	0.26
	(4.78)	(7.15)	(7.10)	(7.15)	(7.12)
Client-Per-MgmtCom2		−0.007	−0.008	−0.008	−0.008
		(−5.15)	(−5.15)	(−5.23)	(−5.26)
MgmtCom-Per-Client	−0.08	0.31	0.30	0.31	0.30
	(−3.47)	(2.10)	(2.02)	(2.07)	(2.05)
MgmtCom-Per-Client2		−0.032	−0.032	−0.033	−0.033
		(−2.78)	(−2.74)	(−2.66)	(−2.64)
Ln-Ave-MgmtCom-Client-Shared-DVol			0.062	0.067	0.10
			(1.88)	(1.99)	(2.54)
StockCumDGTW_20TrdDays				8.68	9.39
				(3.83)	(3.32)
MgmtCom-Ave-ResESF					−0.152
					(−2.16)
Pseudo-R^2	0.107	0.148	0.156	0.161	0.174
SMP	17,406	17,406	17,406	17,406	17,406
N	142	142	142	142	142

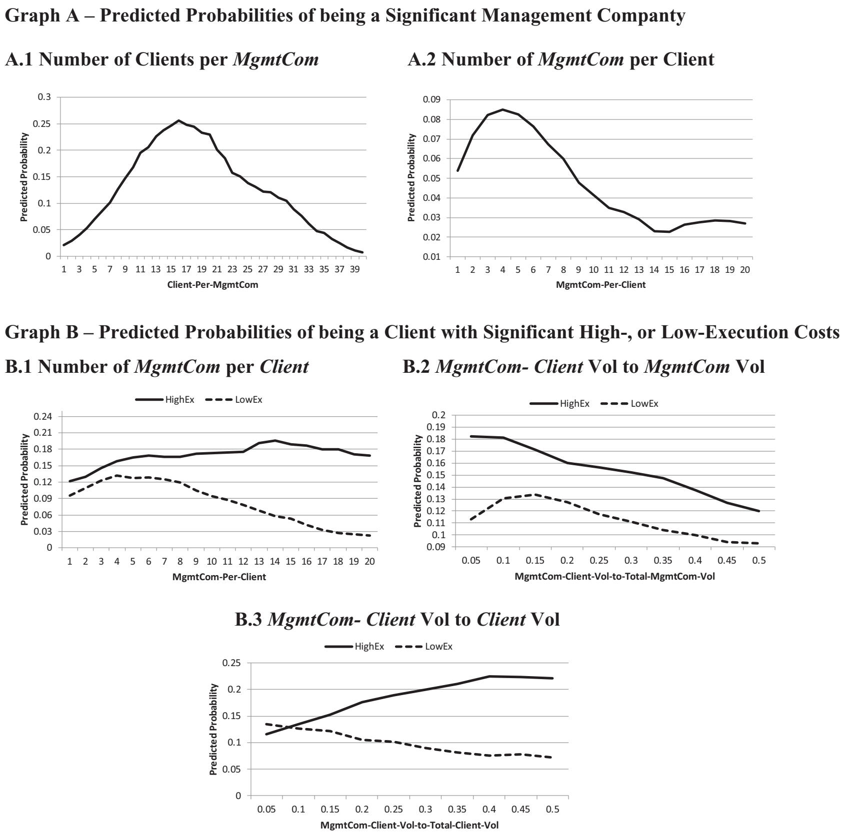

Figure 2. Predicted probabilities of significant management companies and significant clients. The figure depicts predicted probabilities from Table IX's and X's probit model estimations. Graph **A** depicts the predicted probabilities of being in the significant MgmtCom based on the number of clients per MgmtCom (**A.1**) and number of MgmtComs per client (**A.2**) using Specification 2 of Table IX. Specifically, we set the control variables to their means and vary our variable of interest based on the sample range. For example, the average minimum and maximum of the number of clients per MgmtCom are 1 and 40, respectively. In a similar manner, the average minimum and maximum of the number of MgmtComs per client are 1 and 20, respectively. Graph **B** depicts the predicted probabilities of a client receiving significantly high-, or low-execution-cost, based on the number of management companies per client (**B.1**); the ratio of the MgmtCom-Client dollar trading volume to total MgmtCom dollar trading volume (**B.2**); and the ratio of the MgmtCom-Client dollar trading volume to total Client dollar trading volume (**B.3**). All three analyses (i.e., B.1–B.3) use Specifications 2 and 5 from Table X. As in Graph A, we set the control variables to their means and vary our variable of interest based on the sample range.

5.2 Characteristics of High- and Low-Execution Cost Clients

To allow for a fair comparison across clients, we rank clients within the subset of significant management companies into terciles based on their ResESF. We then focus on clients in the top and bottom terciles with statistically significant ResESF. As in Table IX, we use Fama–MacBeth (1973) probit models of 12-month rolling windows, and set the dependent variable to be 1 if the client is defined as a client with significant average ResESF and 0 otherwise. Given that high- and low-execution cost clients may be different in nature, we

Table X. Determinants of clients with significant differences in execution costs

The table reports the determinants of clients that are ranked in the top or bottom tercile within the subset of significant management companies and have statistically significant execution costs. To be included in the sample, a trade must be made by the same MgmtCom for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. These criteria yield 2,011,006 MgmtCom-Client-Day-Stock-Broker trades. As in Anand *et al.* (2013), we use the ESF as our measure of transaction costs. To account for the economic determinants of the execution shortfall, we use the ResESF from a monthly regression of ESF on client's trade volume and other stock characteristics (see Table I for more details). As in Table IX, we use Fama–MacBeth (1973) probit models of 12-month rolling windows, and set the dependent variable to be 1 if the client is defined as a client with a significant ResESF average and 0 otherwise. Given that the nature of high and low execution cost clients can be different, we split the sample into positive ResESF clients (top tercile which has relatively high execution cost) and negative ResESF clients (bottom tercile which has relatively low execution cost). For a fair comparison, we set the middle tercile to be the benchmark for both groups. Significant clients within each tercile ranking are those with *p*-values of less than 5%. To create one cross-section per window, we calculate for each client within a management company the window average of each of the explanatory variables of interest. We then run cross-sectional probit models (i.e., one observation per MgmtCom-Clinet pair, per window) and report the time-series average of the model coefficients and their associated *t*-statistics. While the definition of significant management companies is based on the shared trade sample, some of the explanatory variables are based on the entire set of trades reported in ANcerno. Specifications 1–3 (4–6) analyze the sample of the relatively high execution (low execution) clients. In all specifications, the prefix Ln refers to the natural log of the explanatory variable, and the suffix 2 refers to the variable squared. For example, Ln-MgmtCom-Client-Shared-DVol is the natural log of MgmtCom-Client-Shared-DVol. Pseudo-R^2 is the probit model's pseudo R^2. SMP is the number of MgmtCom-Client observations used in the regressions. The *t*-statistics listed below the regression coefficients are adjusted for serial correlation using the Newey–West (1987) correction using 12 lags.

	HighExc			LowExc		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ln-Client-Total-Dvol	−0.117	−0.049	−0.075	−0.037	−0.191	−0.162
	(−0.61)	(−0.51)	(−0.79)	(−0.44)	(−1.22)	(−1.14)
MgmtCom-Per-Client	0.063	0.107	0.131	−0.026	0.218	0.221
	(1.11)	(2.44)	(2.16)	(−2.73)	(1.89)	(2.01)
MgmtCom-Per-Client2		−0.005	−0.006		−0.021	−0.020
		(−1.67)	(−1.69)		(−2.27)	(−2.12)
MgmtCom-Client-Vol-to-Total-MgmtCom-Vol	−0.358	2.340	2.291	−0.269	5.964	4.094
	(−0.51)	(2.75)	(2.42)	(−1.22)	(1.91)	(2.51)
MgmtCom-Client-Vol-to-Total-MgmtCom-Vol2		−12.600	−11.749		−27.211	−16.214
		(−3.49)	(−3.17)		(−2.11)	(−2.33)
MgmtCom-Client-Vol-to-Total-Client-Vol	0.708	3.934	4.078	−0.951	1.199	−1.502
	(3.23)	(4.38)	(4.26)	(3.14)	(0.89)	(−0.77)
MgmtCom-Client-Vol-to-Total-Client-Vol2		−4.706	−5.011		−8.719	−9.308
		(−3.14)	(−3.12)		(−1.75)	(−1.19)
Ave-MgmtCom-Client-Stock-Trade-Gap			0.001			−0.019
			(0.91)			(−2.98)
Pseudo-R^2	0.064	0.116	0.129	0.061	0.114	0.141
SMP	7707	7707	7707	8110	8110	8110
N	142	142	142	142	142	142

perform separate analyses on the high-execution cost clients (top tercile of ResESF) and low-execution cost clients (bottom tercile of ResESF). We set the middle tercile group to be the benchmark for both groups. Also, to have one cross-section per window, we calculate the window average of each of the explanatory variables of interest for each client within a management company. We then estimate the cross-sectional probit models and report the time-series averages of the coefficient estimates together with their *t*-statistics.

Table X reports the results. Specifications 1–3 (4–6) report results for clients with high (low) execution costs. In all of our specifications, we make sure to control for the client's total dollar trading volume (i.e., across all management companies). In particular, we explore how competition in the form of management companies per client affects the probability of receiving low or high execution costs. In addition, focus on the amount of trading volume being processed for a given client at a given management company and across other management companies.

As in Table IX, a non-linear specification seems to better capture the dynamics between clients and management companies. Figure 2, Graph B.2, provides a clear interpretation of the predicted probabilities. Graph B.1 indicates that, as the number of management companies increases, the probability of receiving low execution costs increases. At some point, as the number gets too large, the probability decreases. On the other hand, the probability of receiving high execution costs monotonically increases with the number of management companies managing the client's portfolio. This is consistent with a low-attention explanation.

Focusing on the amount of trading volume processed via management companies, Figure 2, Graph B.2, shows that the probability of being a low-execution cost client increases with trading volume. This suggests that the more revenue the client brings to the management company, the higher the probability of receiving lower execution costs. Interestingly, when volume is large enough, the likelihood of receiving either high or low execution costs drops. Finally, Figure 2, Graph B.3, indicates that clients who are more reliant on a given management company to execute their trades are more likely to be high-execution cost clients. This is intuitive, since if the client is already heavily invested in a management company, higher trading costs will be less important for it. In sharp contrast, the probability of being a low-execution cost client decreases with the importance of the management company to the client. Again, if a client is already heavily invested, there is no incentive for the management company to put greater effort into execution. Finally, Specifications 3 and 6 explore whether clients with shorter investment horizons or shorter-term trading strategies are more likely to care more about trading costs. In particular, for each client–management company pair, we calculate the average trading gap between two transactions in a given stock (Ave-MgmtCom-Client-Stock-Trade-Gap). We find that clients with lower trading gaps are more likely to receive lower execution costs.

6. Conclusion

The execution costs associated with billions of dollars' worth of daily trades are important to both institutional investors and their asset management companies. While earlier research has focused on direct trading costs, such as effective spreads and price impact measures, the availability of trading data allows for the exploration of broader aspects of execution and differences in execution ability across management companies (Anand *et al.*, 2012).

In this paper, we add to the literature by exploring the variation in execution across clients within management companies, using a proprietary database which includes detailed daily trading data for management companies' trades on behalf of their institutional clients. We focus on a set of trades made by management companies for more than one institutional client for the same stock, on the same day, in the same direction (i.e., buy or sell) and executed by the same brokerage firm. This allows us to focus on execution efforts across clients and largely eliminate potential conflicting explanations such as trading desk skills, liquidity, trading style, and stock-picking abilities.

Using the shortfall measure, we find systematic differences in execution costs across clients for a subset of management companies. These differences are substantial and comparable in magnitude to the variation in trading costs across management companies.

We explore potential explanations for the observed differences in trading costs. In particular, whether these differences are a result of an intentional behavior by the management company or unintended consequence of client's different trading practices. The overall evidence is more consistent with an intentional behavior in the form of allocation of execution costs.

Finally, trading the same stock for multiple clients is an integral part of management companies' daily trading activity—a natural result of sharing similar information with and managing correlated portfolios across clients. Given the economic significance of the variation in execution across clients documented in this paper, this aspect of execution should be taken into account by market participants regardless of the ultimate source of the differences.

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