Are Some Clients More Equal than Others?
Evidence of Price Allocation by Delegated Portfolio Managers

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Abstract

We use daily trades of management companies on behalf of their institutional clients to provide direct evidence of strategic price allocation. Focusing our attention on a subsample of "bunched trades" – a management company's trades of the same stock, on the same day, in same the direction, for more than one client – we find that some clients receive systematically better prices than others. Average magnitudes can be as large as 0.50% of dollar trade volume. We find that clients who benefit outperform their counterparts by 0.15% per month and reward managers with a 15% - 30% increase in trading volume. This paper is the first to provide direct evidence of strategic performance allocation, and to reveal a new channel that could not previously be tested.

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1 Introduction

A new line of research exploring conflicts of interest at the management company level provides evidence of strategic performance allocation across clients (E.g., Gaspar, Massa and Matos (2006) and Chaudhuri, Ivkovic and Trzcinka (2013))[1,2,3] Though the evidence is compelling, there are at least two reasons why further investigation is needed: (1) Due to the lack of availability of transaction-level data, the analysis is usually conducted using account-level returns which have been aggregated across time and across individual securities; (2) It is not clear whether the two main channels of performance allocations suggested in the literature – IPO allocation and cross-trading – occur frequently enough to explain the observed transfer of performance, or whether there are other, previously unidentified channels. In this paper, we use a unique database of the daily trades of management companies on behalf of their institutional clients to provide ***direct evidence*** of strategic performance allocation, and offer ***a new channel*** which is an integral part of the daily trading activity of many management companies.

Delegated portfolio management companies often mention in their ADV filings to the SEC that they tend to buy or sell the same stocks for multiple clients on the same day. This is a natural result of sharing similar information and managing correlated portfolios across clients (see Elton,

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[1] Gaspar, Massa and Matos (2006) provide evidence that mutual fund families strategically transfer performance across member funds to favor those more likely to increase the overall family profits (i.e., funds with high fees or high past performers). Examining the institutional money management industry, Chaudhuri, Ivkovic and Trzcinka (2013) find evidence of strategic performance allocation, directed toward strong recent performers and dominant clients.

[2] Papers examining other types of performance allocation and other distortions resulting from management companies' principal-agent conflicts are: Massa (2003), Nanda, Wang, and Zheng (2004), Gaspar, Massa and Matos (2006), Guedj and Papastaikoudi (2008), Bhattacharya, Lee and Pool (2012), Chaudhuri, Ivkovic and Trzcinka (2013), and Goncalves-Pinto and Schmidt (2013).

[3] Conflicts at the management company level are different than conflict at the individual fund level. Examples of conflicts at the fund level include: Tournament affects (e.g., Brown, Harlow and Starks (1996) and Kempf and Ruenzi (2008)), risk shifting (e.g., Brown, Harlow and Starks (1996), Koski and Pontiff (1999), Goetzmann, Ingersoll, Spiegel and Welch (2007) and Huang, Sialm, and Zhang (2011)), price manipulation and window dressing (e.g., Lakonishok, Shleifer, Thaler, and Vishny (1991) and Carhart, Kaniel, Musto and Reed (2002)) and late trading (Chalmers, Edelen and Kadlec (2001)), and Gastineau (2004)).

Gruber and Green (2007), and Blocher (2011)). When buying or selling the same stocks for multiple clients, management companies have incentives to take into consideration the overall execution of these trades. For example, aggregating (or "bunching") these daily trades into a single order may lead to smaller transaction costs or commissions, and may reduce administrative costs.[4] However, given the inherent principle-agent conflict, there are also potential costs to clients from aggregating trades, since management companies may have incentives to treat clients differently. Because managers typically have several hours after orders are filled to allocate shares to clients, there is potential for managers to engage in "strategic price allocation" (hereafter, "*SPA*"), which we define as the allocation of different prices to different clients involved in a "bunched" (same stock, same direction and same day) trade which systematically favors one client over the other. *SPA* may be especially tempting considering that management companies have diversified sets of clients such as mutual funds, corporate pension and profit-sharing plans, and high net worth individuals.

To test for *SPA*, we take advantage of a fairly new proprietary database provided by Ancerno Ltd., which includes daily trades of delegated portfolio managers on behalf of their institutional clients. We provide direct evidence that a significant fraction of management companies engage in *SPA* and show that the impact is economically significant. We explore the characteristics of the management companies and clients likely to be involved and provide evidence of the benefits from these allocations to the favoring management companies and favored clients. Finally, we rule out alternative hypotheses which might explain our results.

[4] Examples of this motivation can be found in management companies' ADV filings. Example 1: "*Where [the firm] buys or sells the same security for two or more clients, [the firm] may place concurrent orders with a single broker, to be executed together as a single 'block' in order to facilitate orderly and efficient execution.* … Example 2: "It is generally [*the firm*] or its affiliates' practice, when appropriate, to combine or "bunch" orders of various accounts… Bunched orders may be executed through one or more brokers."

Without the use of trade-level data, *SPA* would be very difficult to detect. The Ancerno database covers a diversified set of managers, most of whom have multiple clients. Moreover, many clients have more than one management company – a practice common in the pension fund industry.[5] Using the client-management company links provided by Ancerno, we exploit this rich, multiple-links structure to test for strategic price allocation.

When trades are bunched, allocated prices may differ for purely random reasons or could vary systematically across clients. It's possible that the latter may occur for reasons other than strategic price allocation. To test these possible scenarios in an orderly manner we define our hypotheses as the following: our null hypothesis (H1) there are no ***systematic*** differences in prices across clients; the *SPA* hypothesis (H2) systematic differences across clients are driven by strategic performance allocation; the alternative hypothesis (H3) systematic differences across clients are driven by different trading practices (and not favoritism). We construct our tests based on this order. In particular we examine: 1) whether some clients systematically receive better prices than others, 2) whether there are systematic differences between clients within management companies. 3) the characteristics of management companies likely to engage in *SPA*, and the characteristics of clients who systematically receive better or worse prices than others, 4) the economic benefits to management companies and clients likely to be involved, 5) alternative explanations which are consistent with the different trading practices hypothesis.

Our approach is simple. We focus on the sub-sample of "bunched trades" on a given day across the clients within each management company. Specifically, we define bunched trades as trades by a single management company in the same stock, on the same day, and in the same

[5] Examples of studies investigating the pension industry are: Lakonishok, Shleifer, Thaler, and Vishny (1991), Goyal and Wahal (2008), Busse, Goyal and Wahal (2012), Jame (2012), and Chaudhuri, Ivkovic and Trzcinka (2013).

direction (i.e., buy or sell) for more than one client.[6] For most of the analysis, we focus on trades with different prices, but we also examine bunched trades with equally allocated prices.[7] It is important to note that using a sample of trades of the same stock executed by the same management company allows us to control for unobservable variables such as stock picking ability and trading desk skills.

For each client we calculate a profit measure which captures the difference between its actual allocated trade price and the same trade price across all clients in the bunched trade (i.e., a hypothetical same price benchmark). Using these price differences we calculate each client's profit-to-trade-volume measure (hereafter, "*PTV*") based on the client's volume in the bunched trade. For each Client-Manager pair we calculate an average *PTV*.[8] Importantly, we find twice as many statistically significant average *PTV*s as would be expected under a random allocation benchmark.[9] The ballpark economic magnitude of *PTV* is between 0.10% to 0.50% of dollar trading volume, depending on the client's age and type of trades.[10] For comparison, the average transaction cost in Ancerno's sample is around 0.10%. Given that (1) the economic magnitude of *PTV* is 1 to 5 times as large as transaction costs, and (2) the set of clients in our sample are those who are concerned enough about transaction costs to subscribe to Ancerno's services, these price differences are economically significant. Moreover, because we only observe the set of clients in Ancerno's database, the *SPA* we observe is a lower bound.

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[6] Management companies may have many reasons to execute trades with a single or multiple brokers. Since we cannot observe the execution decision process - but can observe the outcome of these decisions - in our main analysis we do not limit ourselves to trades which are executed by the same broker.

[7] Only one-fourth of the dollar value of bunched trades is allocated to all clients at the same price.

[8] We use "Client-Manager pair" and "Manager-Client pair" interchangeably throughout the paper.

[9] We simulate 10,000 random samples by randomly reshuffling the clients in each Manager-Day-Stock bunched trade to create the random allocation null benchmark. This benchmark accounts for the type of manager, stock characteristics, client structure and time in sample.

[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.

We next explore the differences between clients within a given management company. Starting with in-sample tests, we rank clients within management companies based on their *PTV* averages and test whether these differences are statistically significant. Similar to the previous tests, we calculate the significance levels based on a simulated random allocation benchmark. Here, we find that the number of management companies with statistically significant differences is between two to three times the amount expected under a random allocation benchmark. We continue with out-of-sample tests. Specifically, using a 12-month rolling window, we split our managers into two groups – significant and non-significant – based on the statistical significance of the difference between their clients' *PTV*s. Strikingly, we find strong evidence of out-of-sample persistence in price allocation for the significant manager group and no evidence of persistence for the other manager group. This result can be clearly seen in Figure 2. Additionally, we apply parametric and non-parametric tests including portfolio ranking and cross-sectional Fama-MacBeth regressions. These results are robust regardless of which test is applied.

Having established the existence of systematic differences in price allocation across clients among a significant subset of portfolio managers, we next explore the characteristics of managers likely to be involved. Specifically, we are interested to learn whether these characteristics are consistent with the strategic performance allocation hypothesis (H2). Utilizing Fama-MacBeth Probit models to estimate the probability that a manager is in the statistically significant group, we find that managers whose clients hold similar portfolios, hold stocks across more industries, and have higher shared volume are more likely to be in the significant group. Furthermore, we find that managers with more clients and managers whose clients have fewer managers tend to be in the significant group.

Next, we examine the characteristics of the clients who are likely to be affected by price allocation. We find that clients with high relative volume in bunched trades are less likely to have statistically significant *PTV*s. On the other hand, clients whose portfolios overlap with more clients under the same manager, and who trade illiquid and volatile stocks, are more likely to be in the significant group. In addition, having fewer total managers increases the likelihood of being favored. In contrast, clients with more managers are more likely to bear the costs of *SPA*.

The characteristics of the management companies and clients likely to be involved are consistent with our SPA hypothesis. Still, an important economic aspect of the *SPA* is the benefits that accrue to both the managers and clients. Following this point we explore the existence of such benefits. Examining the significant managers group, we find an increase of 15%-30% in trading volume by favored clients. By contrast, we do not find significant changes in volume by the disfavored clients. Strikingly, when we explore the non-significant mangers group, we do not find any statistically significant changes in dollar volume. Thus, managers engaging in *SPA* are able to attract more volume from favored clients while avoiding a reduction in volume from other clients. Next, using a proxy for trade gains we find that the significant positive clients outperform their counterparts by 0.15% per month. This average is statistically significant with a *t*-statistic of 1.98. Again, we do not find such a result for the disfavored clients, which may suggest that the cost is shared across clients (the trade gains average is -0.02% with a *t*-statistic of 0.27).

Although our collective tests support the *SPA* hypothesis, there could still be alternative explanations for our findings. To rule out these concerns, we examine three alternatives. First, we test whether our results are simply driven by "directed brokerage arrangements" in which clients direct the manager to execute their trades with a specific broker. These arrangements might lead to worse order execution for affected clients. To rule out this explanation, we restrict the sample of bunched trades to those that are executed by a single broker. This reduces our sample by more than half, but we find similar results, suggesting that our findings are not explained by directed brokerage arrangements.

The second possible alternative is management companies' potential use of complex compensation schemes which may take trade commissions into account. While unlikely, it is possible that clients that pay larger broker commissions are compensated by the manager with better prices. To rule out this explanation, we rank clients with the same management company by both commissions and *PTV* and find that that there is no significant difference in *PTV* between clients paying high commissions and clients paying low commissions. Thus, price allocation is not simply a compensation for transaction costs.

The third potential explanation is client heterogeneity within a management company, which might lead to different execution practices. To rule out this explanation, we first show that our results are not driven by a simple price impact explanation (i.e., larger trades are always last in line). Next, we show that clients' portfolios within management companies are similar. Finally, we show that clients do not different in their fill rates. Thus different execution practices driven by differences in clients do not drive our results.

Our results contribute to the broader literature on strategic performance allocation, and conflicts in management companies in general. Importantly our paper is the first to use actual transaction-level data of management companies on behalf of their institutional clients to explore such behavior. Furthermore, our paper sheds light on a new and important channel that was previously ignored by the literature. This channel, which is a by-product of the trading process, provides ample opportunities for managers to transfer performance between clients.

The rest of the paper is organized as follows. Section 2 describes the trading environment, data, and measures. Section 3 presents the empirical results regarding systematic price allocation. Section 4 presents the empirical findings regarding the determinants of managers and clients and their benefits. Section 5 explores alternative explanations. We conclude in Section 6.

2. Trading Environment, Data and Summary Statistics

2.1 Trading Environment

Management companies have a diversified set of clientele. For example, a given management company's clients may include mutual funds, trusts, estates, corporate pension and profit-sharing plans, charitable institutions, high net worth individuals, corporations and other business entities.

Because delegated portfolio managers often make similar trades across clients, they may find it convenient to aggregate (or bunch) similar trades across clients for cost savings and other reasons.[11] As management companies often mention in their ADV filings, bunched trades (same stock for different clients) may be processed with a single broker or multiple brokers, depending on trade size.[12] Clients' orders are typically sent to the management company's trading desk who 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 trades (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

[11] In our sample, the degree of overlap in trades between clients under the same management company is high (see Table 1). For institutional investors' overlap in stock holdings, see Elton, Gruber and Green (2007), and Blocher (2011).
[12] In general smaller trades tend to be executed with one broker. We verify that this is the case in our sample.

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 fills are sent to back to the trading desk, which then allocates the fills to its clients based on its own discretion (the brokerage firm doesn't know how these trades are allocated). Trades are typically sent to the clients' custodian banks by the end of the trading day.

When allocating the fills, a management company may choose to give each client the same price based on the overall bunched trade. However, the company may also choose other options such as an allocation based on the price impact, pre-determined random order, rotational order, or based on any other objectives for specific clients.

It is important to note that trading practices are complicated. Trading factors such as price, size and difficulty of execution, might affect a specific execution. As a result, management companies often state in their ADV filings that clients may receive different prices when the company executes similar trades and that best execution should not be measured by a single transaction. Importantly, management companies also typically specify that any differences should not persist over time. Thus, although observing different prices within a given bunched trade is likely, we shouldn't expect to find systematic differences between clients.

2.2 Data

2.2.1 Ancerno's Institutional Trading Data

We obtain institutional trading data from January 1999 to September 2011 from Ancerno Ltd. Ancerno (formerly a unit of Abel/Noser Corp) is a widely recognized consulting firm that provides consulting services to institutional investors which help them monitor their trading costs.[13]

As mentioned in Puckett and Yan (2011) (hereafter, "PY") and Franzoni and Plazzi (2013) (hereafter, "FP"), Ancerno's data have several appealing features for academic research. First, Ancerno's data are released in monthly batches and are not updated after their release. Thus, survivorship bias is not likely to be an issue. Second, given that the purpose of Ancerno's service is transaction cost analysis and not performance it is also safe to assume that the data are free of self-reporting bias. Third, the data do not include trades occurring before the client formed its relationship with Ancerno. Thus, the data seem to be free of backfill bias. Finally, PY find that the characteristics of stocks held and traded by Ancerno's institutions are not significantly different from the characteristics of stocks held and traded by the average 13F institution. PY estimate that Ancerno institutions account for 10% of all institutional trading volume which represents a significant fraction of total institutional trading volume.

2.2.2 Bunched Trades Sample

Similar to FP we receive identification codes from Ancerno which enable us to link clients to their management companies. These links are crucial to our study since we explore management companies' trades across clients. To the best of our knowledge, Ancerno made these links available for academic research only recently for a short period of time.[14] Thus,

[13] Previous studies that use Ancerno data include: Anand, Irvine, Puckett and Venkataraman (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 (2013), Goldstein, Irvine, and Puckett (2011), Huang, Tan and Wermers (2013), Jame (2013), and Puckett and Yan (2011).

[14] It is important to note that our analysis ends at September 2011 since Ancerno has decided to scrub the data from this point forward.

previous studies using Ancerno data were unable to explore the dynamics between clients within the same management company and across management companies.

Our data include the following identification codes: *Clientcode,* a unique numerical code given to all Ancerno clients. The identity of the clients is not revealed; *Clienttype*, classifies clients as pension plan sponsors, mutual funds, and brokers based on Ancerno's internal classification; *Managercode*, a unique numerical code given to the management company. 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 manager. As mentioned in FP, clients usually find it convenient when reporting to Ancerno to partition their relation with a manager into several categories. Our analysis does not require this variable, since we examine bunched trades at the management company level.

Our main variables include: the date of trade (*YY/MM/DD*), the stock ticker and *CUSIP*, the number of shares per trade, the execution price of a trade and a Buy or Sell indicator which specifies whether a trade is a buy (1) or a sell trade (-1). A detailed explanation about Ancerno variables can be found in the PY Appendix. In general, each observation in the database describes a trade made by a management company on behalf of its client. If it takes more than one trade to complete a client's order, the data includes all partial executions. Each execution is a line in the data. For our purpose we aggregate the client's "intraday trades" at the daily level. To keep a record of the number of trades needed to complete the client's order, we create a variable which counts the number of transactions used and use that variable as a control.

Our objective is to investigate how bunched trade prices are allocated across clients sharing the same trade. In our main tests, we define bunched trades as trades by a management company for more than one client in the same stock, on the same day, and in the same direction.[15] In Section 5.1, we use a more strict definition by further requiring such trades to be executed by the same broker. Appendix A provides an example of a bunched trade made by a management company on behalf of its clients. In this example, the management company trades the same stock on the same day and in the same direction (i.e., buy or sell) for its 5 clients. In the spirit of this example, we only include trades that are a part of a general trade made by the management company for more than one of its clients. We term this sample as *SDDP*, which stands for Same-Direction-Different-Price. Finally, it is important to note that besides the natural multiple links from management companies to clients, there are also multiple links from clients to management companies. The latter case occurs when the client is a plan sponsor or a pension plan, since a pension fund's total portfolio may be managed by multiple management companies.

We match our sample to CRSP using both stock's ticker and *CUSIP*. To ensure the match is made correctly, we require Ancerno's daily close-price variable to match CRSPs close-price for any given trade. We exclude from our sample managers with code 0 that cannot be matched with clients. We also exclude one major client which has significant changes in its time-series links to the management company codes in the middle of its sample. After applying these filters, our initial data contains 39,597,396 Manager-Client-Day-Stock trades which are executed via 204,944,704 partial trades. Recall, that to be in our bunched trade sample, we require managers to include more than one client in the same trade. As a result, we are left with 6,125,606 Manager-Client-Day-Stock bunched trades translating into 1,938,525 Manager-Day-Stock trades. Based on these numbers, the average number of clients in a bunched trade is 3.21. Although these trades account for around 16% of the observations (i.e., 39 million vs. 6 million),

[15] Management companies may have many reasons to execute trades with a single or multiple brokers. Since we cannot observe the execution decision process - but can observe the outcome of these decisions - in our main analysis we do not limit ourselves to trades which are executed by the same broker.

the average volume processed is around 50% (25%) of the equally (value) weighted clients' total monthly volume. It is important to note that these ratios are unconditional ratios based on the entire sample. Calculating these statistics based on the sub-groups of the significant managers and clients (which demonstrate systematic price differences) yield much higher averages. The trades are executed via 488 different management companies and 825 different clients, which translates to 5,144 different Manager-Client pairs. We use the terms "Client-Manager" and "Manager-Client" interchangeably throughout the paper.

Importantly we analyze trades in the same stock and in the same direction on a given day which are executed by the same management company and even by the same brokerage firm (Section 5). Using this specific sample allows us to control for unobservable variables such as stock picking ability, broker talent and trading desk skills.

2.3 Profit-to-Trade-Volume (PTV) Measure

We construct a new measure to explore the existence of price allocation. Consider Appendix A's example in which trade prices differ across clients. Under the assumption of same price benchmark (hereafter, "*SPB*"), each client should receive the same price. We calculate that price by dividing the total bunched $ volume of all clients by the total number of shares bought or sold. Using the *SPB*, we compute each client's hypothetical profit or loss as the difference between its actual price and the same price. We then construct the Profit-to-Trade-Volume (hereafter, "*PTV*"). Specifically, we define *PTV* as:

$$[\#\text{ of shares} * (\text{Actual Price} - SPB) / (\$\text{ Volume})] * \text{SignOfTrade} * (-1) \qquad (1)$$

Note that the profit component, [# of shares * (Actual Price – *SPB*)], is a zero sum game, adding up to 0 at the bunched trade level. To reflect the gains or losses we multiply the sign of trade by -1. For example, in Appendix A, client #1's *PTV* is calculated as [(500 *($47.02-$47.06))/$23,510] *1*(-1) = 0.00085, reflecting a trade gain of 0.085%.

2.4 Sample Statistics

Table 1 reports the sample statistics for selected variables used in our analysis. For each variable we calculate the time-series average of the monthly cross-sectional statistics. For example, Mean (SD) is the time-series average of the cross-sectional Mean (SD). As mentioned management companies in our sample manage more than one client, and a client can have more than one management company. Consider the monthly-based variable first. The average number of clients per manager is 5.16, with a standard deviation of 4.83. The number of managers per client is lower, with an average of 3.45. The average number of bunched transactions per month is 47 over an average of 21 different stocks. To measure the degree of portfolio overlap between clients with the same management company, for each month and client, we count the number of traded stocks that are similar to at least one of the other clients in that group and divide that number by the total number of different stocks trades by the client. The equally (value) weighted average overlap ratio is 83% (42%), which indicates that there is a large degree of similarity between the clients' portfolios. This overlap measure is calculated based on all client's trades (i.e., bunched and non-bunched). In a similar manner, the ratio of monthly bunched dollar volume to the client's monthly total dollar volume is 50%. If we account for volume, and calculate the volume-weighted average across clients, the ratio drops to 25%, suggesting that high volume clients have lower ratios. Considering the client's age, the average number of bunched-trade months of a Client-Manager pair is 27 months. The average number of months considering all trades (bunched and non-bunched) is 34 months.

The average number of clients in a bunched trade is 3.21 with a standard deviation of 2.23. We also learn that the average number of trades needed to complete a bunched trade (i.e., partial trades) is 5.65, and that the average volume-per-trade is around $570,000. Both variables are highly skewed and Winsorized at 1% of their distribution. Finally, the absolute *PTV* in our sample is around 0.076%, with a standard deviation of 0.332%. Because price allocation is only possible when a bunched trade is filled at different prices, we hypothesize that *PTV* may be correlated with volatility. To explore this relation, we create a range measure using the prices within a bunched trade. Specifically for any bunched trade, we calculate the difference between the high and low prices, and normalize it by the average trade price. We term this measure as *H-L*. Figure 1 plots the time series relation between the *H-L* monthly cross sectional average of and the *VIX* levels. The graph clearly indicates that the *PTV* opportunities are related to volatility. The correlation between *H-L* and *VIX* is 0.82.

3. Significance and Persistence in *PTV*

3.1 Significance of Client-Manager Pairs

As mentioned in Subsection 2.1, different prices for different clients in a given bunch may occur randomly. Thus it is important to explore whether these differences are systematic. If price differences occur in a systematic manner, they could be driven by different reasons. To test these possible scenarios in an orderly manner we set our hypotheses are as follows: our null hypothesis (H1) there are no ***systematic*** differences in prices across clients; the *SPA* hypothesis (H2) systematic differences across clients are driven by Strategic Performance Allocation; the alternative hypothesis (H3) systematic differences across clients are driven by different trading practices (and not favoritism). We construct our tests based on that order.

Motivated by hypothesis H1, we begin by exploring the systematic behavior of price allocation. Specifically, in this section we examine whether some managers systematically allocate better/worse prices across clients. If we reject H1 and find systematic differences across clients, there could be a few possible explanations for our findings (i.e., H2 or H3). We control for clients' sample frequency by conducting the analysis at the monthly level. Specifically, we calculate each client's equally weighted monthly *PTV* measure.[16] We begin our investigation by calculating the Client-Manager *PTV* averages and their statistical significance. We then explore differences in clients' *PTV*s within management companies and examine their statistical significance. Finally, we explore the out-of-sample persistence of these differences. To account for an appropriate random allocation benchmark, we simulate random samples and use their distributional properties in our tests.[17]

Table 2 reports the percentage of Client-Manager pairs with significant *PTV* averages. We present results for different frequencies and different *p*-value cutoffs. Consider first the "2 and above" columns which are results for Client-Manager pairs with at least 2 months in the sample. There are 4,739 Client-Manager pairs that meet this criterion. If we look at the 10% *p*-value cutoff, there are 16.16% of Client-Manager pairs with similar or lower *p*-values. To account for a random benchmark we determine the Client-Manager significance level by using a simulated benchmark. Specifically, to create a distribution under the null hypothesis of same price

[16] Value-weighted monthly averages yield similar results.
[17] Other examples of papers using simulated benchmarks are: Kosowski, Timmerman, Wermers and White (2006), and Fama and French (2010).

allocation, we simulate 10,000 random samples by reshuffling the clients in each Manager-Day-Stock bunched trade. Randomly reshuffling at the Manager-Day-Stock level, allows us to account for the type of stock, time and manager characteristics for each client. For each simulated sample we calculate the average *PTV* and its *p*-value and store that information. We then use the distribution of each Manager-Client pair to locate the nominal *p*-value in that distribution. The use of simulated *p*-values slightly reduces the number of significant cases to 14.75%. In a similar manner, the number of significant cases under the 5% *p*-value cutoff is almost double what one would expect under the null. Importantly, the significance levels are stable when we require the Client-Manager pair to have at least 6 or 12 monthly observations. Thus, our results are not sensitive to the number of months in which clients appear in the sample.

Splitting the sample into positive and negative averages reveals the number of positive and significant Client-Manager pairs is always larger than the number of negative and significant pairs. The ratio between positive and negative significant pairs ranges between 1.29 and 1.49 depending on the cutoff and frequency used. Consistent with the *SPA* hypothesis, these ratios may suggest that the burden of price allocation is shared with more clients, thus there are fewer negative and significant clients. Because these costs are lower and shared across more clients, they may be more difficult for a given client to detect than the benefits. This intuition is similar to that in Chaudhuri, Ivkovic and Trzcinka (2013), who provide evidence that those bearing the costs of "performance allocation" in the institutional money management industry are less likely to notice the transfer of performance than are those receiving the subsidy.

Table 3 presents the economic magnitude of Table 2's significant clients' *PTV*s at the 10% *p*-value cutoffs for different frequencies.[18] Panel A uses all daily trades to calculate the monthly *PTV*. Note that the magnitude of the average *PTV*s decrease with frequency for both positive and negative clients. As in Table 2, the ratio of the number of positive to negative clients is greater than one, and ranges between 1.4 and 2. Interestingly, this ratio increases monotonically with the time in the sample. This suggests that the persistence of the positive clients is stronger; probably because negative costs are better spread across clients. Considering the magnitudes of the positive clients, the average *PTV* for the 1 to 12 month frequency is around 0.13% (0.35%) for the average (90th percentile). Interestingly, the magnitude drops by 50% to around 0.06% (0.15%) for longer frequencies. The negative client columns present similar results. Inspired by Figure 1, we next explore whether managers favor the same clients when they have more opportunities. Keeping Panel A's clients, Panel B calculates the *PTV* averages, using only trades that are above the monthly *H-L* cross sectional average. Importantly, it seems that conditioning on trades above *H-L* the same clients receive better allocations. The magnitudes of the average *PTV* for the first 12 months jump to 0.274% (0.614%) for the average (90th percentile).

Table 3 clearly indicates that magnitudes (both positive and negative) decrease over time. These results are consistent with the *SPA* hypothesis (H2) and not with the different trading practices hypothesis (H3), since under H3 we shouldn't expect these differences to diminish over time. Thus, the results suggest that management companies' incentives to subsidize a favored client are strong when these clients are new, but once a relationship has been established, the subsidy is reduced. Management companies tend to avoid exploiting specific clients for extended periods of time, which may reduce the likelihood of client departures.

[18] We find qualitatively similar results when we measure the frequency based on the time in months of each Client-Manager's monthly history.

3.2 Significance between Clients within Management Companies

The next set of tests explores whether there are significant differences between clients within management companies. Table 4 begins with a simple **in-sample** test. For each management company we keep the top and bottom clients and calculate the *p*-value for the difference in averages. To account for the in-sample selection when choosing the top and bottom clients, we simulate the null benchmark. Specifically, we simulate 10,000 random samples by reshuffling the clients in each Manager-Day-Stock bunched trade. For each simulated sample we calculate the difference between the *PTV* averages of the top and bottom clients and their associated *p*-value. We then use each manager's distribution to locate the nominal *p*-value in that distribution. The results clearly indicate that such a correction is necessary. The nominal *p*-values are subject to selection bias. However, the simulated *p*-values still provide strong evidence of price allocation. All simulated *p*-values indicate that there are between 2-3 times more significant cases then expected under a random price allocation.

Table 5 continues with **out-of-sample** persistence tests using Fama-Macbeth cross-sectional correlations and regressions of *PTV* on lagged *PTV*. For each month *m*, we use a rolling window of 12 calendar months from *m-12* to *m-1* (hereafter, "*Ranking-Window*") to calculate the Client-Manager *PTV* averages, and the *p*-values of the difference in averages between the managers' top and bottom clients. For each *Ranking-Window*, we define the significant managers as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level (see Table). For each of the 141 out-of-sample months we calculate the time series averages of the monthly cross-sectional tests. Consider the cross-sectional correlation tests. Clearly, the magnitude of the correlations increases as we move from a calculation based on all Client-Manager pairs (ALL) to one based on the significant managers (SigM) only. Specifically, the correlations increase from 0.033 to 0.261. Repeating these tests with cross-sectional regressions including manager fixed effects yields similar results. Because these are out-of-sample tests, these results provide strong evidence of the persistence of price allocation within significant management companies.

Figure 2 provides further evidence of the persistence presented in Table 5. Specifically, we start with non-parametric out-of-sample tests. Using the *Ranking-Window* from Table 5, we rank the clients within a management company into quartiles based on the ranking period *PTV*s (*Ranking-Quartiles*). For each of the 141 out-of-sample months, we then re-rank the clients into quartiles based on month *m's PTV* averages (*Post-Ranking-Quartiles*). Graph A plots the *Post-Ranking-Quartile* averages based on the *Ranking* quartiles. The significant managers clearly exhibit persistence in their out-of-sample ranking, while the non-significant managers ranking is flat, showing no persistence. Graph B plots the average *PTVs* for the *Ranking* and *Post-Ranking* periods, where Graph B.1 (B.2) plots the averages of the significant (non-significant) managers. In each graph, *RankPTV* (*PostPTV*) is the *Ranking-Window* (*Post-Ranking) PTV* average. Both groups present similar *PTV* magnitudes during the *Ranking-Window*, with average *PTV*s ranging between -0.15% (Quartile 1) and 0.15% (Quartile 4). Contrastingly, the non-significant managers *PTV* averages are around 0 regardless of the *Ranking-Window* quartile, while the significant managers present persistence, with *Post-Ranking PTV*s ranging between -0.05% and 0.07%.

Following Graph 2B, Table 6 presents the average PTVs of managers' top and bottom clients from the *Ranking* and *Post-Ranking* periods. These two periods are formed by dividing the monthly *PTV* observations of each client in half. We then define the first period as the *Ranking* period, and the second period as the *Post-Ranking* period, which allows us to look at changes in each specific client's *PTV* during its sample period. We calculate the average *PTVs* and difference between the top and bottom clients for each manager based on the clients' *Ranking-Period*. As in Table 5, we define the significant managers during the *Ranking-Period* as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level. Using this information we calculate the averages and differences between the top and bottom clients during their *Post-Ranking* period.

Similar to Graph 2B, we present results for the significant and non-significant managers. The results reinforce the findings in Graph 2B. Both groups have similar *PTV* magnitudes during their *Ranking-Period*s. This is expected since the top and bottom clients are chosen in-sample. Strikingly, there is evidence of reversal in the non-significant manager group. Five out of Six ratios between the *Ranking* and *Post-Ranking* periods are negative. The significant managers, on the other hand, present persistence ranging between 39% and 62%, and *PTV* averages between 0.063% and 0.123% depending on the frequency used. Following Table 3 – keeping the same clients – we calculate the *PTV*s based on trades with above average *H-L*. Similar to the findings in Table 3, this strengthens the results. The persistence ranges between 48% and 100% and the *PTV* averages are between 0.153% and 0.278%. Similar to Table 3 these results are consistent with the *SPA* hypothesis (H2) since these magnitudes should not diminish or reverse if they are a result of differential trading practices.

To summarize, we provide evidence which rejects H1. Namely, there are systematic differences across clients and within a subset of management companies. Moreover, part of the analysis presents results which are consistent with the *SPA* hypothesis. The next section will explore the *SPA* hypothesis in more detail.

4. Determinants of Significant Managers and Clients and Their Benefits

Having established the existence of systematic price allocation we further investigate the *SPA* hypothesis. Specifically, this section examines the determinants of those managers likely to engage in price allocation, and the determinants of the clients being favored, as well as those bearing the costs. In addition we explore the benefits accruing to the favoring management companies and the benefits to the favored clients, providing evidence that both parties stand to gain.

4.1 Determinants of Significant Managers

We use Table 4's *p*-value cutoffs to identify the subgroup of significant managers. Our dependent variable is set to 1 if a manager is in the significant manager group and 0 otherwise. We run monthly cross-sectional Probit models, and calculate the time-series averages of the model estimates. The models are estimated at the manager level with 24,902 Manager-Month observations (i.e., one observation per management company, per month). Since we don't know the identities of individual managers and clients, our variables are limited to those that we can construct using Ancerno's trading data. As mentioned, we have multiple links between management companies and clients (for example, a pension fund can manage its portfolio using more than one management company). Thus, we use the number of clients per manager, and the number of managers per client as explanatory variables. The number of clients per manager may be a proxy for manager opportunities across clients. Similarly, the number of managers per client may be a proxy for the type of client.

Table 7 presents the results. Panel A presents results from multivariate analysis. For robustness Panel B presents results from a univariate analysis. Panel B indicates that the selection order of the explanatory variable doesn't affect the estimated coefficients. As a result, we discuss only Panel A's results. Consider specification (1). The number of clients per manager has a positive coefficient. Managers with more clients are more likely to be participating in price allocation. This probably reflects the opportunity set of the management company. Together with the findings from Tables 2 and 3, this suggests that management companies are able to hide the costs of price allocation by spreading them across multiple clients. Those with fewer clients are less able to do so. The average number of managers per client has a negative coefficient which means that management companies whose clients have multiple managers are less inclined to favor one client over the other.

Specification (2) indicates that managers with larger shared volume are more likely engage in price allocation. The shared volume might reflect opportunities from two aspects: more bunched trades and larger price impact from the trades. Specification (3) indicates that overlap in trades between clients is also an important determinant. Again, the more clients trading the same set of stocks, the greater the ability to engage in price allocation. Specification (4) includes the average number of industries per client. The coefficient is positive, which indicates that industry-diversified clients have more opportunities for price allocation. Finally, specification (5) examines nonlinear versions of clients per managers and mangers per client. Interestingly, when we add the squared term into the estimation, both variables load positively on the first term and negatively on the second term. Consider the clients per manager variable. The increase in clients seems to be positive up to a point after which it begins to decrease. In a similar fashion, the average number of managers per client has a positive effect up to a point. However, firms whose clients have a large number of managers are less likely engaging in price allocation.

To illustrate the non-monotonic relation between manager significance and the number of clients per manager and managers per client, we plot the predicted probabilities of manager significance in Graph A of Figure 3. Specifically, we set the other control variables to their means and vary our variables of interest based on the sample range. For example, the average min and max of the number of clients per manager are 1 and 40, respectively. In a similar manner, the average min and max of the number of managers per client are 1 and 20, respectively. Graph A.1 (A.2) plots the predicted probabilities of being in the significant manager group based on the number of clients per manager (managers per client) using Table 7 Specification 5. As predicted, the probability of being a significant manager increases with the number of clients per manager up to a point and then decreases. The maximum is around 8 clients per manager. Above that point, having more clients reduces the probability of being a significant manager. As for the number of managers per client, the probabilities are relatively stable for values up to 6. For more than 6 managers per client, the predicted probabilities sharply decline.

To summarize, the characteristics of the significant managers are consistent with the *SPA* hypothesis. Managers whose clients hold similar stock portfolios, hold stocks across more industries, have higher shared volume, and have fewer other managers are more likely to be in the significant group.

4.2 Determinants of Significant Clients

In this subsection we take advantage of the methodology used in subsection 4.1. Specifically, we group clients into significant and non-significant Client-Manager pairs. The significant levels are based on Table 2's *p*-value cutoffs. Specifically, our dependent variable is set to 1 if a Client-

Manager pair is in the significant group and 0 otherwise. Importantly, because the characteristics that determine which clients are positive and significant may differ from those explaining negative significance, a separate estimation might be warranted. To address this point, we split the sample into positive and negative *PTV* clients, as done in Table 2. Similar to subsection 4.1, for each sub-sample we estimate monthly cross-sectional Probit models, and calculate the time series averages of the model estimates. The models are estimated at the Client-Manager-Month level (i.e., one observation per Client-Manager pair, per month).

In addition to the explanatory variables used in Table 7, we use the bunched trades in each month to identify the characteristics of the clients' portfolio. Specifically, for each stock traded in a given month we calculate the following variables: the natural logarithm of Size (*LnSize*), the half-bid-ask-spread (*HBAS*) (Amihud and Mendelson 1986, 1989), the standard deviation of monthly returns (*SD*), the natural logarithm of the industry adjusted book-to-market ratio (*LnBM-Ind-Adj*), and the Beta from the market model estimated using monthly returns.[19] To capture the characteristics of the Client-Manager portfolios, for each month *m*, we calculate the variables' volume-weighted averages, using stock characteristics calculated at the end of month *m*-1.

In addition, we create a proxy for clients' gains (or losses) from trading activity (hereafter, "*TradeGains*"). Specifically, for each Client-Manager-Stock triplet we calculate the percentage difference between the net accumulated cash flows during a given period and the end-of-period position value.[20] To calculate the gains (or loses) of the Client-Manager's traded portfolio, we

[19] We retain all observations in our sample and apply Pontiff and Woodgate's (2008) approach to missing BM values. In addition, following Cohen and Polk (2008) we adjust the BM values by their industry average.

[20] For example, suppose that the trades during a given period are as follows: 1,000 shares at $100, -500 shares at $90, and 500 shares at $100, and the end-of-period price is $100. The net accumulated cash flows are $105,000 and the end-of-period value of the stock position is $100,000. Thus, the net trade loss is ($100,000-$105,000)/$105,000

calculate the trade-volume-weighted average using all traded stocks (or open positions). We acknowledge that this measure is a very noisy proxy since Ancerno's dataset doesn't include Client-Manager's holding positions.

Specifications (1)-(5) and (6)-(10) of Table 8 are based on the positive and negative client samples, respectively. The specifications are symmetric in their structure, thus sequential comparisons can reveal possible differences between the positive and negative clients. Comparing Specification (1) and (6), we can observe that for both types of clients, the relative volume in trades has a negative and significant coefficient. A major client's price should converge to the same price (by definition), reducing the magnitude of the *PTV*. The Client-Manager shared volume has a positive and significant coefficient for both types of clients; indicating that larger volume in bunched trades is translated into bigger opportunities of price allocation. Interestingly, the overlap ratio is positive significant for the positive clients and not significant for the negative clients. That asymmetry may indicate that the cost of price allocation is spread across the negative clients. Comparing the coefficients of Manager-Per-Client and Manager-Per-Client squared in both samples, the coefficients load in opposite directions. Consider the positive sample first. The probability of being the beneficiary of SPA is higher for clients with fewer managers. This probability then decreases with the number of managers per client. The result is intuitive since management companies have incentives to subsidize important clients (i.e., clients who have fewer managers managing their portfolio). These incentives naturally decline with the number of managers per client. Similar dynamics are observed in the negative sample; the probability of being a significant negative client is lower for clients with fewer managers. This probability then increases with the number of managers per

= ~ -4.75%. If the number of shares is constant during the estimated period, the calculation is based on the price change. Prices and shares are adjusted for splits and dividends using the CRSP adjustment factors.

client. Again, this result is intuitive since management companies have incentives to shift performance from clients with many managers. Moreover, the number of managers-per-client may be a proxy for the degree of client sophistication or client attention. For example, clients with fewer management companies may be more attuned to the actions of a specific management company. Clients with many managers may be less likely to notice the actions of any specific manager and less likely to notice any costs of SPA.

To illustrate the non-monotonic relation between managers per client and both positive and negative client significance, we plot the predicted probabilities of client significance in Graph B of Figure 3. Similar to Graph A of Figure 3, we set the other control variables to their means and vary our variables of interest based on the sample range. Graph B.1 (B.2) depicts the predicted probabilities of being a significant positive client (significant negative client), based on the number of managers per client, using the specifications with the full set of control variables from Table 8. As predicted, the probability of being a positive and significant client increases with the number of managers per client, where the estimated max is around 8. Moreover, these probabilities then sharply decrease when the number of managers per client increases. Interestingly, the graph of the negative and significant clients is more modest, suggesting that the cost is shared across clients. Importantly, as expected, the probability of being a negative and significant client increases when the number of managers increases.

To test if price allocation is translated into better performance, we use our *TradeGains* proxy (Specifications (2) and (7)). Specifically, for each month m we calculate this measure based on a rolling window of 12 months (using shorter intervals yield similar results). Interestingly there are differences between the positive and negative samples. The measure is positive and significant in positive sample and not significant in the negative sample. A positive and significant coefficient means that the relative performance is higher for the positive and significant clients (relative to their counterparts). As for the negative clients, the insignificant result suggests that the burden is spread across different clients. In an un-tabulated result, for each Client-Manager pair, we calculate the monthly *TradeGains* measure and find an average difference in performance of 0.15% per month between the positive-significant clients and their counterparts. Consistent with the regression results, we do not find such a difference for the negative sample.

Next, exploring the effects of size, liquidity and volatility, Specifications (3) and (8) indicate that clients that trade illiquid stocks are more likely to be significant in both directions. Illiquid stocks tend to have bigger price differences which should lead to more opportunities for price allocation. Interestingly, Size does not seem to be significant in the positive sample, and is positive and significant for the negative sample. Adding the volatility, Specifications (4) and (9) indicate that standard deviation is also an important driver, which is consistent with Figure (1). Finally, Specifications (5) and (10) indicate that the clients are not different in their beta and growth opportunities.

To summarize, the characteristics of the significant clients are consistent with the *SPA* hypothesis. Clients with low relative volume in bunched trades, whose portfolios overlap with more clients under the same manager, with fewer managers and who trade in illiquid and volatile stocks are more likely to be the beneficiaries of price allocation.

4.3 Benefits

So far our evidence suggests that there are systematic price differences across clients within a subset of management companies. Subsection 4.1 and 4.2 provide additional evidence consistent with the economic story of price allocation (H2). Still another important part of the story is the benefits from allocation behavior to the management companies and the favored clients. In this Subsection we provide evidence that both managers and favored clients benefit when they engage in *SPA*.

4.3.1 Benefits to Management Companies

Managers are only likely to engage in *SPA* if they expect to benefit. Such benefits may be direct (e.g., an increase in volume by the favored clients which increases management fees) or indirect (e.g., the reputation of managing a star product). Since we cannot observe the indirect benefits, we test for direct evidence. Specifically, we explore the change in trading volume by favored and disfavored clients over time. We follow Table 6's sub-period analysis and we replace the *PTV* variable with change in trading dollar volume. We examine each client's total trades (i.e., bunched and not bunched).

As in Table 6, we calculate the change in trading volume between sub-period 1 and sub-period 2 for the top and bottom clients within each management company, and then we analyze these changes for the significant and non-significant manager groups. Starting with the significant managers group, we find that top clients increase their volume by 15%-30% during the second sub-period. These changes are statistically significant. By contrast, the bottom clients do not present any statistically significant change in their trading volume. Moreover, the differences between the top and bottom clients are statistically significant. Strikingly, the non-significant management companies do not present any significant trend.

We repeat the analysis using cross-sectional regressions of change in volume between period 1 and 2 on period 1's *PTVs*. We find consistent results. Specifically, we find positive and statistically significant coefficients for the significant manager group and non-significant coefficients for the non-significant manager group. The asymmetric response by clients shown in these two tests is consistent with Table 2 which shows that managers spread the costs of *SPA* across more clients than the benefits, and provides strong evidence that managers stand to gain from these transfers.

4.3.2 Benefits to Clients

If positive and significant clients benefit from price allocations we should see an increase in their performance. Since our data do not include the holding position we instead track the clients' trading performance. In Subsection 4.2 (and footnote 17) we presented our *TradeGains* proxy which reflects gains from trading activity. In this subsection we calculate this proxy for every month using all trades of each client-manager pair. Following Table 8's analysis, we compare each subgroup with its counterpart (i.e., positive and significant clients with positive, non-significant clients and negative and significant clients with negative, non-significant clients). Using this measure, we find that significant positive clients outperform their counterparts by 0.15% per month on average with a *t*-statistic of 1.98. By contract, we do not find that the significant negative clients outperform or poorly perform their counterparts. The average is -0.02% with a *t*-statistic of 0.27. This suggests that the negative cost is shared across clients.

To summarize, in this subsection we provide evidence which is consistent with our *SPA* hypothesis. We find an increase in volume by the favored clients within the significant management companies, and find positive trading gains for the positive and significant clients.

4.4 The Probability of Observing Different Prices

Thus far, our sample has included only Same-Direction-**Different-Price** bunched trades and has ignored Same-Direction-**Same-Price** bunched trades, where management companies assign the same price to all clients. There are a few reasons one might observe the same prices in a bunched trade. In some cases, the transaction may have been small enough to be completed in one trade without imposing a price impact. On the other hand, it could have been the conscious decision of the management company to assign the same price to all clients sharing that trade. In this sub-section, we examine the probability of observing a trade with different prices vs. one with the same price. ***For this test only*** we combine our main *SDDP* sample with a second sample of bunched trades with ***same prices***. To be included in the second sample a trade must be part of a general trade made by the management company for more than one client. The trade must be in the same stock, on the same day, in the same direction (i.e., buy or sell) with the ***same price***. We term this sample *SDSP*, which stands for Same-Direction-Same-Price. Similar to Panel 1A, Panel 9A reports the time-series averages of the monthly cross-sectional statistics of the *SDSP* sample during January 1999 to September 2011, a total of 153 months.

Our *SDSP* sample contains 3,804,319 Manager-Client-Day-Stock trades which are executed via 10,823,232 partial trades. The Manager-Client-Day-Stock trades are bunched into 1,651,801 Manager-Day-Stock trades. Based on these numbers, the average number of clients in these bunched trades is 2.30. Although these trades account for around 46% of the *SDDP+SDSP* observations, the average volume processed is only around 25% of the clients' *SDDP+SDSP* monthly volume. The volume per trade variable is consistent with that finding. The average volume per trade is $291,000 compared to $571,000 in panel 1A. Similarly, the number of clients-per-manager, managers-per-client, and other trade statistics are lower.

Panel B reports the time-series average of the cross-sectional monthly Probit model coefficients and their associated *t*-statistics. The model is estimated at the Manager-Day-Stock level, where the dependent variable receives the value of 1 if a bunched trade is with different prices and 0 otherwise.

Specifically, Panel B of Table 9 presents 5 different specifications used to estimate these probabilities. Specification (1) is at the manager-bunched transaction level; Specification (2) is at the Manager-Month level; Specifications (3) and (4) are at the Manager-Client-Month level with and without Manager Fixed Effects; and Specification (5) runs Manager-by-Manager cross-sectional regressions for each year and month. Importantly, all specifications present similar results. The probability of observing a trade with different prices increases with: the number of clients in the bunched trade; the number of intraday trades needed to complete the client's transactions; and with the volume per trade. These results make sense, since large trades, more clients sharing a trade and split transactions are more likely to result in different prices during a trade execution.

5. Alternative Explanations

Our tests so far support the *SPA* hypothesis. There are systematic differences across clients, and the characteristics and benefits are consistent with the *SPA* economic story. Still, there may be alternative expansions which could potentially explain our findings.

In this section, we explore whether there are other possible mechanisms that might explain our results. We consider three possible alternative explanations. The first is “directed brokerage arrangements” where clients direct the manager to execute their trades with specific brokers. Managers who are directed by a client to use a specific broker may not be able to deliver the best price execution. The second is a complex compensation scheme by management companies which takes trade commissions into account. According to this explanation, clients who pay higher commissions could be compensated through better execution prices. The third potential explanation is that our results are driven by client heterogeneity within a management company, which might lead to different execution practices. This might include a price impact explanation (i.e., larger trades are executed last) and/or different execution practices driven by different strategies.

To address these concerns, we explore the likelihood of these alternative explanations. We start with the directed brokerage explanation by examining the sub-sample of trades which are executed by the same broker. As for the second alternative explanation, we explore the relation between *PTV* and the trade commissions within a management company. Finally, we explore the relation between trade size and execution price, and the similarity of clients’ portfolios. Importantly, our analysis indicates that the paper’s results are not driven by directed brokerage arrangements, a complex compensation scheme, or client heterogeneity.

5.1. Directed Brokerage Arrangements

We restrict our bunched trade sample to include shared trades that were executed by the same brokerage firm. Specifically, to be in the sub-sample, a trade must be made by the same management company, 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. This restriction reduces the sample of trades from 6,125,606 to 2,478,678 Manager-Client-Stock-Day trades.[21]

First, in an un-tabulated analysis we repeat the analyses in Tables 2 and 4, using the sub-sample of trades, and verify that the significance levels of our sub-sample are qualitatively similar to our full sample. Next, in Panel A of Table 10, we continue and explore the economic magnitude of the *PTV* averages based on frequency. Consider Panel A.1 of Table 10 first. Comparing the magnitudes of the *PTV* averages to Panel A of Table 3 reveals that the sub-sample *PTV* averages are smaller than the averages in our full sample. One possible explanation is less opportunity for price allocation. Since trades executed by the same broker are more likely to be smaller in magnitude and to be executed simultaneously, the option to allocate larger price differences is diminished.[22] Following this argument, in Panel A.2 of Table 10 we re-calculate the *PTV* averages for trades above the monthly H-L averages. The *PTV* averages are 3 times larger on average, which is consistent with the opportunity explanation.

[21] In addition to the broker identification, Ancerno provides other variables which are related to the brokerage firm execution process: the placement time, which is the time when the broker received the ticket; the execution time, which is the time when the broker executed the trades; the market price at the placement, and the market price at the execution. Importantly we find that for the majority of the cases the placement time is 9:30 and the execution time is 16:00 or 16:20. Moreover, on average in 65% of the cases the market price at the placement matched CRSP's opening price. As a result, we cannot use these variables in the analysis.

[22] In an un-tabulated result, we estimate a Probit model where the dependent variable is the probability of observing a trade executed by the same broker. We find that this probability decreases with the number of clients sharing a trade and the dollar volume of trade.

Panels B and C of Table 10 repeat the out-of-sample analyses of Table 5 and 6. Panel B results indicate that the *PTV* persistence is similar in magnitude to the results presented in Table 5. Furthermore, the economic magnitude presented in Panel C is consistent with the results presented in Table 6 – especially when using the “above H-L” averages. Finally, we replicate the analysis in Figure 2 using the sub-sample. Figure 4 depicts this out-of-sample quartile ranking. Consistent with Table 10 results, Figure 4’s graphs are qualitatively similar to the graphs presented in Figure 2.

We further investigate the directed brokerage argument, by directly exploring the tendency of clients to use the same brokerage firm in their trades, during each trading month of our sample. During this analysis we explore all trades available in our data. Interestingly, we find that in only 2% of all the possible client-month pairs are all of a client’s daily trades executed by the same brokerage firm within the given month. Furthermore, if we restrict the clients to the ones with more than one management company the number drops to 0.5%.

To summarize, the collective evidence suggests that our results are not driven by directed brokerage arrangements.

5.2. Complex Compensation Scheme

The second alternative explanation is the potential existence of a complex compensation scheme within management companies. To test this explanation, in Table 11, we explore the relation between the *PTV* and trade commission (hereafter “*TCOM*”) averages. Specifically, for each trade *TCOM* is calculated as the ratio between the dollar commission paid, divided by the dollar trade volume (in %). Panel A of Table 11, we present the *PTV* and *TCOM* averages based on *TCOM* terciles. Specifically, for each month, we rank the clients within each management company (with at least three clients) into three *TCOM* terciles. We then calculate time series averages for both *TCOM* and *PTV*. We explore two specifications: "*ALL*" which uses all management companies, and "*SigMgrs*" which uses the only the significant management companies, as defined in Table 4. The resulting *TCOM* tercile averages range between 0.075% and 0.30%. Interestingly, the *PTV* averages are effectively zero, and the difference between the top and bottom TCOM terciles is not statistically significant.

Next, we explore the other direction by conditioning on *PTV*. Specifically, in Panel B of Table 11, we calculate the *PTV* and *TCOM* averages of the top and bottom (*PTV* based) clients, where the top and bottom clients are defined in Table 4. Similar to Panel A, "*ALL*" ("*SigMgrs*") is a specification that uses all of the (only the significant) management companies. To control for possible time trend we calculate the averages only for overlapping top and bottom clients' observations, although the results are qualitatively similar when we use all observations. Since we condition on *PTV*, the differences between the top and bottom clients are statistically and economically significant. Importantly, the differences in *TCOM* are practically zero and not significant. Since both panels suggest that there is no relation between *PTV* and trade commissions, we can rule out that our results are driven by a compensation for differences in trade commissions.

5.3. Client Heterogeneity within a Management Company: Price Impact, DGTW scores, Trading Style and Fill Rates

In the final set of tests, we show that our results are not driven by heterogeneity in clients which might affect the execution prices within a bunched trade. For example, because larger trades may have more price impact, clients who are allocated larger quantities may mechanically be allocated worse prices. Additionally, clients whose overall portfolios differ may receive different attention within a given bunched trade.

Price impact: If managers take price impact into account, clients with larger trades should be allocated worse prices. To test for a possible price impact story, we calculate the correlation between share quantities and execution prices for each management company and each bunched trade. In this test we examine bunched trades with at least 3 clients. We find significant correlations for only 3.5% of the management companies. Importantly the number of positive and negative significant correlations is similar. Moreover, counting the mere number of positive and negative correlations (regardless of their significance level) indicates that 53% (47%) of the cases are negative (positive). Thus a price impact story doesn't seem to drive our results.

Trading Style: if significant clients are different from other clients within a management company, different execution practices might drive our results. Specifically, it could be that unique strategies required by a client might be translated into different prices within bunched trades. To rule out this possibility, we explore the similarity between significant and non-significant clients within a management company using two measures: the DGTW stock ranking as suggested by Daniel, Grinblatt, Titman and Wermers (1997) and Trading Style (TS) as suggested by Anand, Irvine, Puckett and Venkataraman (2013). Importantly, using both measures, we do not find any statistically significant differences between the significant clients and their counterparts. This is probably not surprising given the high degree of overlap in trades presented in Table 1.

Fill rates: if some clients' trade executions are more urgent, it may be reflected in the daily fill rates. Since Ancerno does not provide the actual fill rates, we create a measure which reflects the trade continuation over the next day. Specifically, for each client in each bunch trade, we look at the total traded shares during day-0 (the bunched-trade date) and day-1 (the following day). We then calculate day-0 fill rate as the ratio between stocks bought or sold on day-0 and the total stocks bought or sold during days 0 and 1. Using this measure we test whether clients are different in their realized fill rates. For example, client A may have an average fill rate of 90% while client B may have an average fill rate of 50%. Thus, it could be that the price differences are driven by the importance level of trade execution across clients. Importantly, we do not find any statistically significant differences between the significant clients and their counterparts.

6. Conclusion

We use a fairly new proprietary database which includes daily trading data of management companies on behalf of their clients to directly examine how management companies allocate the prices of bunched trades between their clients.

We define a bunched trade as a trade made by the management company 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. This sample structure allows us to control for unobservable variables such as stock picking, manager talent, trading desk skills and brokerage skills.

Using a new measure which captures the client’s losses or gains from a given bunched trade, we find clear evidence indicating that different clients systematically get different prices. The gains and losses can be as large as 0.50% of dollar trading volume. We find significant differences between clients within the management company. Importantly, out-of-sample tests indicate that these price differences are persistent. We also provide results regarding the characteristics of management companies likely to engage in price allocation, and the clients with significant gains and losses. Consistent with the strategic performance allocation hypothesis, we find that clients who benefit outperform their counterparts by 0.15% per month and reward their managers with a 15% - 30% increase in future trading volume.

Finally, we explore three alternative explanations, directed brokerage arrangements, the existence of complex compensation schemes, and client heterogeneity within management companies. Our tests indicate that the paper's findings are not driven by these possible explanations.

In the broader context, our findings support the literature on management companies' strategic behavior (e.g., Massa (2003), Nanda, Wang, and Zheng (2004), Gaspar, Massa and Matos (2006), Chaudhuri, Ivkovic and Trzcinka (2013), among others), by providing direct evidence of strategic performance allocation using trade-level data, and introducing a new channel that has been ignored by the previous literature. Importantly, this paper explores one of many potential channels for strategic performance allocation. Future research will explore other important channels that can only be detected using transaction level data.

Appendix A- Bunched Trades with Different Prices

Appendix A, presents an example of a bunched trade made by a management company on behalf of its clients. To be in our bunched trade sample, a trade must be part of a general trade made by the management company for more than one client. The trade must be in the same stock, on the same day, in the same direction (i.e., buy or sell) with different prices. We term this sample *SDDP*, which stands for Same-Direction-Different-Price. *NumTRD* is the number of trades required to complete the client's transaction. *NumSHR* is the number of shares bought or sold on behalf of the client. *$Vol*, is the dollar volume of the trade. *PRC* is the price associated with each client's trade. *Same Price Benchmark* is a hypothetical price in the scenario where the management company allocates the same price to all clients sharing the trade; calculated as the sum of all clients' *$VOL* divided by the sum of all shares bought or sold.

Manager	*DATE*	*Stock*	*Client*	*NumTRD*	*Num SHR*	*$ VOL*	*PRC*
MGR1	1/1/2010	S1	1	1	500	23,510	47.02
MGR1	1/1/2010	S1	2	1	500	23,530	47.06
MGR1	1/1/2010	S1	3	1	500	23,530	47.06
MGR1	1/1/2010	S1	4	1	1,000	47,080	47.08
MGR1	1/1/2010	S1	5	2	2,000	94,120	47.06
Same Price Benchmark					4,500	211,770	47.06

Appendix B – Variable Definition

Appendix B reports and defines the variables used in the paper's analysis. "Abbreviations" presents the abbreviations used in the paper. "Ancerno's monthly based variables" presents the monthly based variables constructed using Ancerno data. "Ancerno's daily based variables" presents the daily based variables constructed using Ancerno data. "CRSP based variables" presents the variables constructed using CRSP data. *BASE* is the base of the variable calculation. For example, *Client-Per-Manager* is calculated for each month at the manager level (*Mgr*). *Cnt-Trd-Relative-Vol* is calculated for each stock and day, at the Manager-Client pair level *(Mgr-Cnt-D-S*). We use "Client-Manager" and "Manager-Client" interchangeably.

Variable	Definition	BASE
Abbreviations		
PTV	Profit to Trade Volume, calculated using Eq. 1	
Mgr	Manager	
Cnt	Client	
SDDP	Same direction different price	
SDSP	Same direction same price	
M	Month	
Mgr-M	Manager-Month	
Mgr-Cnt-M	Manager-Client-Month	
Mgr-Cnt-D-S	Manager-Client-Day-Stock	
	Number of different stocks shared per client-manager pair	
Ancerno's monthly based variables		
Cnt-Per-Mgr	Number of clients per manager	Mgr-M
Mgr-Per-Cnt	Number of managers per client	Cnt-M
Num-Trd-In-Mon	Number of the monthly shared transactions per client-manager pair	Mgr-Cnt-M
Diff-Stocks-Shared-In-Month	Number of different stocks shared per client-manager pair	Mgr-Cnt-M
Mgr-Cnt-Shrd-Vol	Client-manager pair's monthly shared $ volume	Mgr-Cnt-M
Overlap-Ratio	Number of overlapping stocks per client with other clients within the same management company. The measure is calculated using all client's trades	Mgr-Cnt-M
SDDP-Vol-to-Total-Vol	Monthly shared SDDP volume to Total Trade volume ratio	Mgr-Cnt-M
Months with Shared Trades	Number of months with SDDP trades	Mgr-Cnt-M
Months with All Trades	Number of months with trading activity	Mgr-Cnt-M
Months with Shared to All Trade Ratio	Months with SDDP trades to months with All trades ratio	Mgr-Cnt-M
Ancerno's daily based variables		
Num-Cnt-Sharing-Trade	Number of clients sharing a trade	Mgr-D-S
Cnt-Trd-Relative-Vol	The client's shared trade volume to total shared trade volume	Mgr-Cnt-D-S
Vol-Per-Cnt-Trade	Client's $ volume per trade	Mgr-Cnt-D-S
Num-Partial-Trds-By-Cnt	Number of intraday partial trades by client per stock	Mgr-Cnt-D-S
H-L	The high and low spread per trade, calculated as (H-L)/Ave(H,L) in %	Mgr-D-S
CRSP based variables		
TradeGains	The percentage difference between to net accumulated cash flows during a given period and the end-of-period position value. Prices and shares are adjusted for splits and dividends using CRSP's adjustment factors.	Mgr-Cnt-S
Size	Size in $ millions, calculated as the number of outstanding shares times the end of month price	Mgr-Cnt-M
HBAS	The half bid-ask spread calculated from the CRSP's daily closing bid and ask quotes based on a rolling window of 12 months	Mgr-Cnt-M
SD	Standard deviation of monthly returns, calculated for each month based on a rolling window of 24-36 months	Mgr-Cnt-M
BM-Ind-Adj	Industry adjusted Book-to-Market ratio as suggested by Cohen and Polk (1998) and Wermers (2004)	Mgr-Cnt-M
Num-FF48-Ind	Average number of different industries per client, based on Fama-French's 48 industry classification codes	
Beta	Beta from the market model based on 24-36 months	Mgr-Cnt-M

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Table 1 – Summary Statistics of the *SDDP* (Same-Direction-Different-Price) Sample

The table reports the time-series averages of monthly cross-sectional statistics for different variables in our share trade sample from January 1999 to September 2011, a total of 153 months. To be in our bunched trade sample, a trade must be part of a general trade made by the management company for more than one client. The trade must be in the same stock, on the same day, in the same direction (i.e., buy or sell) with different prices. We term this sample *SDDP*, which stands for Same-Direction-Different-Price. An example of bunched trade with different prices is in Appendix A. Our main variable of interest is the profit-to-volume (hereafter, "*PTV*") measure. Specifically, for each Client-Manager pair engaging in a bunched trade we calculate the trade's profit to volume (We use the terms "Client-Manager" and "Manager-Client" interchangeably). The *PTV* in turn, is calculated as the difference between the actual trade price and the hypothetical price under same price allocation, calculated by dividing the total shared $ volume of all clients to the total number of shares bought or sold. The measure is presented in %. The definition of the other variables of interest is in Appendix B. In the Table, *Monthly based variables* (*Daily based variables*) specifies the unit of calculation (i.e., at the month or day/transaction level). The Table also reports the number of observations used *N*, and the base used in the cross-sectional calculation.

Variables	Mean	Median	SD	N	Mon CS Base
Monthly based variables					
Cnt-Per-Mgr	5.16	3.47	4.83	25,860	Mgr-M
Mgr-Per-Cnt	3.45	2.69	2.97	38,770	Cnt-M
Num-Trd-In-Mon	46.50	19.81	83.81	135,112	Mgr-Cnt-M
Diff-Stocks-Shared-In-Month	21.25	10.66	36.04	135,112	Mgr-Cnt-M
Overlap-Ratio	83.84	100.00	27.06	135,112	Mgr-Cnt-M
Overlap-Ratio - VW	42.01	35.24	N/A	135,112	Mgr-Cnt-M
SDDP-Vol-to-Total-Vol	53.50	56.85	32.48	135,112	Mgr-Cnt-M
SDDP-Vol-to-Total-Vol - VW	25.52	21.14	N/A	135,112	Mgr-Cnt-M
Num-FF48-Ind	29.17	33.64	11.98	135,112	Mgr-Cnt-M
Num-FF48-Ind-VW	31.21	33.93	N/A	135,112	Mgr-Cnt-M
Months with Shared Trades	26.27	14.00	29.71	5,144	Mgr-Cnt
Months with All Trades	34.02	21.00	33.18	5,144	Mgr-Cnt
Months with Shared to All Trade Ratio	77.53	94.44	29.80	5,144	Mgr-Cnt
Daily based variables					
Num-Cnt-Sharing-Trade	3.21	2.45	2.23	1,938,525	Mgr-Day-S
Num-Partial-Trds-By-Cnt	5.65	1.07	15.95	6,125,606	Mgr-Cnt-Day-S
Vol-Per-Cnt-Trade	571,050	76,750	1,637,927	6,125,606	Mgr-Cnt-Day-S
AbsPTV	0.08	0.00	0.33	6,125,606	Mgr-Cnt-Day-S

Table 2 – Clients' Average *PTV* Significance Levels

The table reports the percentage of Client-Manager pairs with significant *PTV* averages for different *p*-value cutoffs and Frequencies. We use the terms "Client-Manager" and "Manager-Client" interchangeably. To be in our bunched trade sample, a trade must be part of a general trade made by the management company for more than one client. The trade must be in the same stock, on the same day, in the same direction (i.e., buy or sell) with different prices. We term this sample *SDDP*, which stands for Same-Direction-Different-Price. An example of bunched trade with different prices is in Appendix A. Our main variable of interest is the profit-to-volume (hereafter, "*PTV*") measure. Specifically, for each Client-Manager pair engaging in a bunched trade we calculate the trade's profit to volume. The *PTV* in turn, is calculated as the difference between the actual trade price and the hypothetical price under same price allocation, calculated by dividing the total shared $ volume of all clients to the total number of shares bought or sold. The measure is presented in %. Finally, to control for the time in sample when comparing the *PTV* measure across clients and managers, we calculate (for each Client-Manager pair) the monthly equally weighted average *PTV*. We then use the monthly *PTV* series to calculate the Client-Manager pair sample average and *p*-value. *Num-CM-Pairs* is the total number of Client-Manager pairs for the specified frequency filter. *Num-Sig-Nominal-P-Values* is the percentage of significant Client-Manager pairs at the specified significance level based on a standard *t*-test. *Min-Month-Freq* is the minimum number of monthly Client-Manager sample observations required to be included in the sample. *Num-Sig-Simulated-P-Values* is the percentage of significant Client-Manager pairs at the specified significance level based on simulated sample *p*-values. Specifically, to create a distribution under the null hypothesis of same price allocation, we simulate 10,000 random samples by reshuffling the clients in each Manager-Day-Stock bunched trade. Using the Manager-Day-Stock unit, accounts for the type of stock, and time and manager characteristics. For each simulated sample we calculate the average *PTV* and its *p*-value and store that information. We then use each Client-Manager distribution to locate the nominal *p*-value in that distribution. Finally, *Num Po-Neg Ratio* (*Num Sig Po-Neg Ratio*) is the number of positive (positive and significant) Client-Manager to negative (negative and significant) Client-Manager pairs.

Frequency	2 and above			6 and above			12 and above		
P-value	10%	5%	1%	10%	5%	1%	10%	5%	1%
Num C-M Pairs	4739	4739	4739	3827	3827	3827	2902	2902	2902
% Sig Nominal P-values	16.16%	9.77%	4.16%	17.82%	10.72%	4.94%	19.78%	12.41%	6.00%
% Sig Simulated P-Values	14.75%	9.58%	3.14%	15.56%	10.24%	3.53%	16.23%	10.65%	4.00%
Num Pos C-M Pairs	2590	2590	2590	2097	2097	2097	1622	1622	1622
% Sig Nominal P-values	16.99%	11.08%	4.71%	20.10%	12.35%	5.58%	21.82%	13.87%	6.60%
% Sig Simulated P-Values	15.90%	10.23%	3.24%	16.97%	10.97%	3.66%	17.32%	11.34%	4.19%
Num Sig Pos	412	265	84	356	230	77	281	184	68
Num Neg C-M Pairs	2149	2149	2149	1730	1730	1730	1280	1280	1280
% Sig Nominal P-values	13.96%	8.19%	3.49%	15.09%	8.72%	4.16%	17.19%	10.55%	5.23%
% Sig Simulated P-Values	13.36%	8.79%	3.02%	13.85%	9.35%	3.39%	14.84%	9.77%	3.75%
Num Sig Neg	287	189	65	240	162	59	190	125	48
Num Sig Pos-Neg Ratio	1.43	1.40	1.29	1.49	1.42	1.31	1.48	1.47	1.42

Table 3 – Economic Magnitude of Average *PTV*

The table reports the average sample's *PTV* of the significant Client-Manager pairs (as defined in Table 2) at the 10% significance level. We use the terms "Client-Manager" and "Manager-Client" interchangeably. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. Panel A reports the results of the average *PTV* based on all clients' trades. *Frequency* is the number of monthly observations per-client. For example *1-6 months* includes client-manager pairs with 1-6 monthly observations. *Ave* is the cross-sectional average of all clients' averages. *SD* is the cross-sectional standard deviation of the clients' averages. *P10* and *P90* are the 10^{th} and 90^{th} percentile of the cross-sectional averages. *N* is the number of client-manager pairs in each frequency bin. Panel B reports the average *PTV* calculated from bunched trades above the monthly H-L cross-sectional average. The *H-L* in turn, is the bunched transaction's high to low price divided by the average price.

Panel A – All Trades

All Trades	Significant Positive Clients					Significant Negative Clients					Pos-Neg
Frequency	Ave	SD	P10	P90	N	Ave	SD	P10	P90	N	N Ratio
1-6 months	0.137	0.325	0.001	0.413	70	-0.121	0.252	-0.246	-0.001	62	1.129
7-12 months	0.124	0.254	0.002	0.269	70	-0.125	0.195	-0.312	-0.002	51	1.373
12-24 months	0.068	0.115	0.001	0.173	62	-0.058	0.076	-0.190	-0.002	46	1.348
25-36 months	0.062	0.073	0.005	0.158	41	-0.080	0.093	-0.180	-0.011	31	1.323
37-48 months	0.053	0.054	0.004	0.138	53	-0.088	0.149	-0.234	-0.009	37	1.432
49-60 months	0.059	0.144	0.003	0.118	30	-0.045	0.044	-0.114	-0.008	18	1.667
More than 60 months	0.027	0.035	0.003	0.067	86	-0.033	0.035	-0.073	-0.004	42	2.048

Panel B – Trades with H-L Greater than Monthly Cross-Sectional Average

Above HL Ave Rrades	Significant Positive Clients					Significant Negative Clients					Pos-Neg
Frequency	Ave	SD	P10	P90	N	Ave	SD	P10	P90	N	N Ratio
1-6 months	0.278	0.373	0.009	0.568	57	-0.306	0.391	-0.662	-0.042	49	1.163
7-12 months	0.269	0.349	0.047	0.659	65	-0.271	0.241	-0.502	-0.066	44	1.477
12-24 months	0.199	0.229	0.029	0.444	58	-0.202	0.178	-0.458	-0.034	44	1.318
25-36 months	0.189	0.214	0.034	0.428	41	-0.209	0.221	-0.375	-0.043	31	1.323
37-48 months	0.138	0.100	0.014	0.266	53	-0.187	0.200	-0.337	-0.042	37	1.432
49-60 months	0.154	0.154	0.031	0.273	30	-0.131	0.139	-0.316	-0.027	18	1.667
More than 60 months	0.104	0.092	0.016	0.202	86	-0.100	0.072	-0.194	-0.033	42	2.048

Table 4 – In-Sample within Manager Significance Levels

The table reports the percentage of managers with significant differences between their client *PTV* averages for different *p*-value levels and client frequencies. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. Specifically, for each manager we focus on the top and bottom clients based on their sample average *PTV*. We calculate the difference between the top and bottom averages together with the *p*-value of the differences using a standard *t*-test. *Min-Month-Freq* is the minimum number of monthly Client-Manager sample observations required for inclusion to be included in the sample. We use the terms "Client-Manager" and "Manager-Client" interchangeably. *Num-Mgrs* is the total number of managers with top and bottom clients for the specified frequency. *Num-Sig-Nominal-P-Values* is the percentage of significant managers at the specified significance level. *Num-Sig-Simulated-P-Values* is the percentage of significant managers at the specified significance level based on simulated samples. Due to the fact that the top and bottom clients are selected we adjust the null benchmark to account for this selection. Specifically, to create a distribution under the null hypothesis of same price allocation, we simulate 10,000 random samples by reshuffling the clients in each Manager-Day-Stock bunched trade. Using the Manager-Day-Stock unit, accounts for the type of stock, time and manager characteristics. For each simulated sample we calculate the difference between the average *PTV* of the top and bottom clients and their associated *p*-value of that difference and store the information. We then use each manager distribution to locate the nominal *p*-value in that distribution.

Frequency	2 and above			6 and above			12 and above		
P-value	10%	5%	1%	10%	5%	1%	10%	5%	1%
Num Mgrs	455	455	455	361	361	361	337	337	337
Nominal P-values	33.41%	22.42%	10.11%	42.38%	26.59%	13.29%	43.32%	28.49%	13.06%
Simulated P-Values	16.04%	11.65%	3.52%	19.94%	14.40%	4.43%	19.88%	13.65%	4.45%
Num Managers - SimPval	73	53	16	72	52	16	67	46	15

Table 5 - Out-of-Sample Persistence in *PTV*

The table reports results from out-of-sample Fama-Macbeth (1973) cross-sectional correlations and regressions of *PTV* on lagged *PTV* from January 1999 to September 2011, a total of 153 months. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. Specifically, we use a rolling window of 12 calendar months - the *Ranking-Window m-12* to *m-1* - to calculate the Client-Manager *PTV* averages, and the *p*-values of the difference in averages between the managers' top and bottom clients. We use the terms "Client-Manager" and "Manager-Client" interchangeably. For each window, we define the significant managers as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level (see Table 4 for reference). We term these managers the significant managers denoted by *SigM*. Using this information we run for each *Post-Ranking-Month m*, the cross sectional correlation and cross-sectional regressions of the clients' *PTV* on their lagged *PTV*. *All* is based on all Client-Manager pairs. *All-TBC* is based on the top and bottom clients of all managers. *SigM* is the *Ranking-Window* significant managers. *SigM-TBC* is based on the top and bottom clients of the *Ranking-Window* significant managers. *CS-Correlations* columns report the cross-sectional correlations; *FM columns* report the results from the Fama-Macbeth (1973) cross-sectional regressions; and *FM-MGR-Dum* columns include manager fixed effects in the cross-sectional regressions. Each method yields 141 out-of-sample monthly coefficients. The table reposts their time-series averages and their associated *t*-statistics. The *t*-statistics are adjusted for serial correlation using the Newey-West (1987) correction.

Method	CS Correlations				FM				FM - MGR Dum			
Variables	ALL	ALL TBC	SigM	SigM TBC	ALL	ALL TBC	SigM	SigM TBC	ALL	ALL TBC	SigM	SigM TBC
Lag PTV	0.033	0.054	0.188	0.261	0.032	0.048	0.283	0.350	0.035	0.088	0.289	0.416
	2.77	3.30	6.68	7.00	2.27	2.59	5.91	5.54	2.42	4.14	6.15	6.58
Mgr Dummies									YES	YES	YES	YES
N	141	141	141	141	141	141	141	141	141	141	141	141

Table 6 - Out-of-Sample Persistence in *PTV* – Economic Magnitude

The table reports the *PTV* averages of managers' top and bottom clients from *Ranking* and *Post-Ranking* periods. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. Specifically, for each manager we divide the monthly *PTV* observations of each client into two equal periods. We then define the first periods is the *Ranking* period, and the second period as the *Post-Ranking* period, which allows us to look at changes in each specific client's *PTV* during the sample period. We calculate the average *PTVs* and the difference between the top and bottom clients for each manager based on the clients' *Ranking* period. As in Table 5, we define the significant managers during the *Ranking* period as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level (see Table 4). Using this information we calculate the averages and differences between the top and bottom clients during their *Post-Ranking* period. *Min-Month-Freq* is the minimum number of monthly Client-Manager sample observations required for inclusion in the sample. We use the terms "Client-Manager" and "Manager-Client" interchangeably. *Ranking Period* is based on the first half of the clients' sample. *Post Ranking Period* is based on the second half of the clients' sample. *Top Average* is the cross-sectional average of the significant managers' top clients. *Bot Average* is the cross-sectional average of the significant managers' bottom clients. *Diff* is the difference between the top and bottom clients. *Persistence Ratio Top* (*Persistence Ratio Bot*) is the ratio between the top (bottom) clients averages in the *Post-Ranking period* and the *Ranking-Period*.

	NonSigMgrs			SigMgrs			SigMgrs - Above HL Ave		
MinFreq	2	6	12	2	6	12	2	6	12
Ranking period									
Top Average	0.220	0.173	0.116	0.212	0.174	0.114	0.262	0.277	0.224
Bot Average	-0.183	-0.121	-0.100	-0.198	-0.167	-0.116	-0.336	-0.337	-0.236
Post Ranking period									
Top Average	-0.022	-0.002	0.006	0.123	0.069	0.063	0.191	0.278	0.153
T-stat	1.40	0.19	0.67	3.66	4.06	3.68	6.49	3.63	4.93
Bot Average	0.053	0.017	0.024	-0.112	-0.097	-0.071	-0.183	-0.182	-0.112
T-stat	1.85	1.10	3.04	1.82	3.94	5.05	4.73	5.41	4.14
Diff	-0.075	-0.019	-0.018	0.236	0.165	0.134	0.374	0.460	0.265
T-stat	-2.30	1.02	-1.57	3.36	5.55	6.06	7.69	5.50	6.44
Persistence Ratio Top	**-10.1%**	**-1.1%**	4.9%	58%	39%	55%	73%	100%	68%
Persistence Ratio Bot	**-29.1%**	**-13.8%**	**-23.6%**	57%	58%	62%	55%	54%	48%

Table 7 – Determinants of Significant Managers

The table reports the determinants of significant managers using Fama-Macbeth (1973) Probit models. The dependent variable receives the value of 1 if the manager is defined as a significant manager and 0 otherwise. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. The definition of the other explanatory variables is in Appendix B. Specifically, for each manager we calculate the Client-Manager *PTV* average during the entire sample period We use the terms "Client-Manager" and "Manager-Client" interchangeably. Next, we calculate the significance of the difference between the top and bottom clients. We define the significant managers as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level (see Table 4). Panel A (B) presents results from Multivariate (Univariate) analysis. In both panels, the prefix Ln refers to the natural log of the explanatory variable, and the suffix 2 refers to the variable squared. For example, *LnCnt-Per-Mgr* is the natural log of *Cnt-Per-Mgr*, and *Cnt-Per-Mgr2* is *Cnt-Per-Mgr* squared. For each month of the 153 months we run a manager level Probit model (i.e., one observation per management company). *SMP* is the number of manager observations used in the regressions. The table reposts the time-series average of the model coefficients and their associated *t*-statistics. The *t*-statistics are adjusted for serial correlation using the Newey-West (1987) correction.

Panel A – Multivariate Analysis

Variables	(1)	(2)	(3)	(4)	(5)
LnCnt-Per-Mgr	0.131	0.065	0.035	0.029	
	2.85	1.78	0.67	0.54	
LnMgr-Per-Cnt	-0.167	-0.168	-0.177	-0.179	
	5.02	3.62	3.76	3.98	
LnMgr-Cnt-Shrd-Vol		0.058	0.059	0.020	0.023
		4.55	4.50	1.80	1.95
LnOverlap-Ratio			0.181	0.128	0.086
			4.16	2.88	2.21
LnNum-FF48-Ind				0.14	0.13
				10.40	9.08
Cnt-Per-Mgr					0.10
					2.21
Cnt-Per-Mgr2					-0.01
					2.15
Mgr-Per-Cnt					0.08
					3.09
Mgr-Per-Cnt2					-0.01
					3.57
SMP	24,902	24,902	24,902	24,902	24,902
N	153	153	153	153	153

Panel B - Univariate Analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LnCnt-Per-Mgr	0.120						
	2.52						
LnMgr-Per-Cnt		-0.147					
		4.54					
LnMgr-Cnt-Shrd-Vol			0.060				
			10.98				
LnOverlap-Ratio				0.246			
				4.37			
LnNum-FF48-Ind					0.17		
					10.20		
Cnt-Per-Mgr						0.133	
						3.07	
Cnt-Per-Mgr2						-0.008	
						2.44	
Mgr-Per-Cnt							0.118
							6.10
Mgr-Per-Cnt2							-0.013
							5.94
SMP	24,902	24,902	24,902	24,902	24,902	24,902	24,902
N	153	153	153	153	153	153	153

Table 8 – Determinants of Significant Clients

The table reports the determinants of significant clients using Fama-Macbeth (1973) Probit models, where we split the sample into positive *PTV* clients and negative *PTV* clients. The dependent variable receives the value of 1 if the client is defined as a significant client and 0 otherwise. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. The definition of the other explanatory variables is in Appendix B. Specifically, for each Client-Manager pair, we calculate the *PTV* average during the entire sample period and its *p*-value. We use the terms "Client-Manager" and "Manager-Client" interchangeably. We use these averages to split the sample into positive and negative *PTV* clients Next, we define the significant clients as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level (see Table 2). In the Table, *Positive* (*Negative*) refers to positive (negative) *PTV* 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, *LnMgr-Cnt-Shrd-Vol* is the natural log of Mgr-Cnt-Shrd-Vol. For each month of the 153 months we run a Client-Manager level Probit model (i.e., one observation per Client-Manager pair). *SMP* is the number of Client-Manager observations used in the regressions. The panels repost the time-series average of the model coefficients and their associated *t*-statistics. The *t*-statistics are adjusted for serial correlation using the Newey-West (1987) correction.

	Positive					Negative				
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
LnCnt-Trd-Relative-Vol	-0.103	-0.103	-0.142	-0.138	-0.140	-0.072	-0.076	-0.095	-0.102	-0.103
	3.37	3.35	4.24	4.06	4.04	2.07	2.13	2.16	2.14	1.84
LnMgr-Cnt-Shrd-Vol	0.124	0.124	0.157	0.155	0.157	0.109	0.113	0.131	0.146	0.148
	7.54	7.37	8.55	8.42	8.26	7.89	8.12	7.88	7.15	4.36
LnOverlap-Ratio	0.296	0.303	0.323	0.348	0.362	0.010	0.005	0.045	0.090	0.121
	3.34	3.35	3.48	3.74	3.87	0.13	0.07	0.59	1.28	1.73
Mgr-Per-Cnt	0.080	0.080	0.075	0.076	0.076	-0.053	-0.056	-0.068	-0.074	-0.088
	5.07	5.04	4.76	4.77	4.70	3.31	3.41	4.03	4.27	4.16
Mgr-Per-Cnt2	-0.005	-0.005	-0.004	-0.005	-0.005	0.003	0.003	0.003	0.004	0.004
	5.19	5.16	4.86	4.86	4.89	3.00	3.14	3.60	3.85	3.86
TradeGains [-1,-12]		0.004	0.005	0.005	0.005		-0.0004	-0.0001	-0.0002	0.001
		3.08	3.03	3.03	2.99		0.21	0.06	0.09	0.42
LnSize			-0.040	-0.004	0.004			0.110	0.181	0.195
			1.39	0.13	0.10			2.60	4.65	3.44
HBAS			3.574	2.956	2.248			10.599	8.734	5.624
			2.44	1.96	1.58			3.76	3.50	1.11
SD				3.986	5.972				8.135	17.152
				3.83	3.39				3.31	2.01
LnBM-Ind-Adj					0.075					-0.215
					1.01					1.13
Beta					-0.085					-0.692
					0.59					1.24
Mgr Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
SMP	76,953	76,953	76,953	76,953	76,953	57,754	57,754	57,754	57,754	57,754
N	153	153	153	153	153	153	153	153	153	153

Table 9 – The Probability of Engaging in Bunched Trades with Different Prices

The table reports the probability of engaging in bunched trades with different prices using Fama-Macbeth (1973) Probit models. The dependent variable receives the value of 1 if the bunched transaction is with different prices and 0 otherwise. ***For this test only*** we combine our main *SDDP* sample with a second sample of bunched trades with the ***same prices***. To be included in second sample a trade must be part of a general trade made by the management company for more than one client. The trade must be in the same stock, on the same day, in the same direction (i.e., buy or sell) with the ***same price***. We term this sample *SDSP*, which stands for Same-Direction-Same-Price. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. The definition of the other explanatory variables is in Appendix B. For completeness, Similar to Panel 1A, Panel A reports the time-series averages of the monthly cross-sectional statistics of the *SDSP* sample during January 1999 to September 2011, a total of 153 months. Panel B reports the time-series average of the cross-sectional monthly Probit model coefficients and their associated *t*-statistics. Specifically, Panel B presents 5 different specifications used to estimate these probabilities. Specification (1) is at the manager-Bunched Transaction level; Specification (2) is at the Manager-Month level; Specifications (3) and (4) are at the Manager-Client-Month level with and without Manager fixed effects; and Specification (5) runs Manager-by-Manager cross-sectional regressions for each year and month. *SMP* is the number of observations used in the regressions. In all specifications, the *t*-statistics are adjusted for serial correlation using the Newey-West (1987) correction.

Panel A – Summary Statistics of the Same-Direction-Same-Price (*SDSP*) Sample

Variables	Mean	Median	SD	N	Mon CS Base
Comparison to *SDDP* Sample					
SDDP to (*SDDP*+*SDSP*) Vol Ratio	74.45	88.16	30.90	142,126	Mgr-Cnt-M
Monthly based variables					
Cnt-Per-Mgr	4.63	3.05	4.01	23,568	Mgr-M
Mgr-Per-Cnt	3.03	2.29	2.58	36,072	Cnt-M
Num-Trd-In-Mon	33.31	7.81	132.17	110,503	Mgr-Cnt-M
Diff-Stocks-Shared-In-Month	15.92	5.55	38.35	110,503	Mgr-Cnt-M
Daily based variables					
Num-Cnt-Sharing-Trade	2.38	2.00	0.96	1,651,801	Mgr-D-S
Num-Partial-Trds-By-Cnt	2.64	1.02	5.19	3,804,319	Mgr-Cnt-D-S
Vol-Per-Cnt-Trade	290,862	49,705	764,586	3,804,319	Mgr-Cnt-D-S

Panel B – Time-series Averages of Cross-Sectional Probit Models

	Trns	Month	Month	Month	MGR by MGR
Variables	(1)	(2)	(3)	(4)	(5)
Num-Cnt-Sharing-Trade	0.232	0.194	0.063	0.387	1.632
	9.75	8.20	5.52	6.67	7.61
Num-Partial-Trds-By-Cnt	0.032	0.038	0.011	0.016	2.047
	9.66	2.78	4.47	4.65	6.21
Vol-Per-Cnt-Trade ($ millions)	0.041	0.145	0.072	0.094	1.668
	9.12	7.75	8.76	6.96	8.03
Mgr Dum				YES	
Unit of Obs	Mgr-Trns	Mgr-M	Mgr-Cnt-M	Mgr-Cnt-M	Mgr-Trns
SMP	3,588,200	49,352	245,613	245,613	3,588,200
N	153	153	153	153	153

Table 10 – Results Based on the Sub-Sample of Same Broker Trades

The table presents results for the sub-sample of bunched trades that were executed by the same brokerage firm. To be included the sub-sample of same broker trades, a trade must be made by the same management company, 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. This restriction reduces the sample from 6,125,606 to 2,478,678 Mgr-Cnt-Stock-Day trades. In this table, Panels A.1 and A.2 repeat Table 3's analysis; Panel B repeats Table 5's analysis; and Panel C repeats Table 6 analysis.

Panel A.1 - Economic Magnitude of Average *PTV* - All Trades

All Trades	Significant Positive Clients			Significant Negative Clients		
Frequency	Ave	SD	P95	Ave	SD	P5
1-6 months	0.048	0.095	0.215	-0.079	0.226	-0.401
7-12 months	0.042	0.137	0.117	-0.048	0.134	-0.231
13-24 months	0.037	0.206	0.117	-0.039	0.147	-0.267
25-36 months	0.020	0.051	0.110	-0.034	0.119	-0.178
37-48 months	0.011	0.028	0.085	-0.034	0.089	-0.225
49-60 months	0.015	0.045	0.094	-0.031	0.181	-0.106
More than 60 months	0.006	0.028	0.062	-0.075	0.328	-0.111

Panel A.2 - Economic Magnitude of Average *PTV* - Trades with H-L Greater than Monthly Cross-Sectional Average

Above HL Ave Trades	Significant Positive Clients			Significant Negative Clients		
Frequency	Ave	SD	P95	Ave	SD	P5
1-6 months	0.149	0.267	0.691	-0.186	0.398	-0.733
7-12 months	0.137	0.413	0.512	-0.116	0.306	-0.538
13-24 months	0.116	0.263	0.464	-0.122	0.346	-0.926
25-36 months	0.078	0.150	0.323	-0.188	0.382	-0.852
37-48 months	0.026	0.111	0.320	-0.071	0.192	-0.357
49-60 months	0.005	0.082	0.133	0.010	0.223	-0.388
More than 60 months	0.024	0.097	0.176	-0.072	0.201	-0.465

Panel B - Out-of-Sample Persistence in *PTV*

Method	CS Correlations				FM				FM - MGR Dum			
Variables	ALL	ALL TBC	SigM	SigM TBC	ALL	ALL TBC	SigM	SigM TBC	ALL	ALL TBC	SigM	SigM TBC
Lag PTV	0.022	0.001	0.236	0.358	0.031	0.010	0.316	0.419	0.061	0.178	0.403	0.533
	1.64	0.06	5.65	7.35	1.91	0.42	5.38	6.01	1.86	1.95	7.55	7.93
Mgr Dummies									YES	YES	YES	YES
N	141	141	141	141	141	141	141	141	141	141	141	141

Panel C - Out-of-Sample Persistence in *PTV* – Economic Magnitude

	SigMgrs			SigMgrs - Above HL Ave		
MinFreq	2	6	12	2	6	12
Ranking period						
Top Average	0.092	0.070	0.058	0.167	0.133	0.118
Bot Average	-0.090	-0.098	-0.065	-0.156	-0.206	-0.174
Post Ranking period						
Top Average	0.044	0.042	0.053	0.148	0.156	0.201
T-stat	2.81	2.31	2.09	4.31	2.83	2.66
Bot Average	-0.034	-0.067	-0.029	-0.128	-0.143	-0.098
T-stat	1.92	2.38	2.32	2.96	2.32	2.72
Diff	0.078	0.109	0.082	0.276	0.300	0.299
T-stat	3.42	3.26	2.89	5.00	3.84	3.37
Persistence Ratio Top	48%	60%	92%	88%	117%	170%
Persistence Ratio Bot	38%	68%	44%	82%	70%	56%

Table 11 – *TCOM* and *PTV* Averages - within Management Company

The table reports the *PTV* and *TCOM* averages controlling for the management company. The bunched trades sample and the monthly *PTV* measure are defined in Table 2. The trade commission (hereafter, "*TCOM*") is calculated as the ratio between the dollar trade commission and dollar trade volume (in %). Panel A presents results based on *TCOM* terciles. Specifically, for each month, we rank the clients within each management company (with at least three clients) into three *TCOM* terciles. We then calculate the *TCOM* and *PTVs'* time series averages. Top - Bottom refers to the difference between the top and bottom *TCOM* terciles, where the *t*-statistic of the difference is clustered by manager and client. In Panel A, "*ALL*" is a specification that uses all management companies. "*SigMgrs*" is a specification which uses only the significant management companies, as defined in Table 4. Panel B calculates the *PTV* and *TCOM* averages of the top and bottom clients (see Table 4). Similar to Panel A, "*ALL*" ("*SigMgrs*") is a specification that uses all (only the significant) management companies. To control for possible time trends we calculate the averages only for overlapping top and bottom clients' observations. In Panel B, "Top- Bottom" refers to the difference between the top and bottom clients, where the *t*-statistic of the difference is clustered by manager and client.

Panel A – within Manager - *PTV* Averages Based on Trade *TCOM* Ranking

	ALL		SigMgrs	
Groups	*TCOM*	*PTV*	*TCOM*	*PTV*
Com 1 - Bot	0.077	0.007	0.113	0.002
Com 2	0.141	0.001	0.172	0.007
Com 3 - Top	0.295	0.008	0.289	0.005
Top - Bottom	0.218	0.001	0.176	0.004
t-statistic		0.21		0.45

Panel B – within Manager - Top and Bottom Clients' *PTV* and *TCOM* Averages

	ALL		SigMgrs	
Groups	*PTV*	*TCOM*	*PTV*	*TCOM*
Top	0.124	0.140	0.128	0.140
Bot	-0.086	0.140	-0.108	0.142
Tom-Bot	0.210	0.000	0.236	-0.001
t-statistic	5.77	0.04	6.69	0.21

Figure 1 – Time Series of Bunched Trades Price Range and Market Volatility

The figure depicts the monthly average of the *H-L* measure and the end-of-month levels of the VIX measure from January 1999 to September 2011, a total of 153 months. The *H-L* in turn, is the bunched transaction's high to low price divided by the average price, presented in %. The definition of our bunched sample and the monthly *PTV* measure calculation are as defined in Table 2.

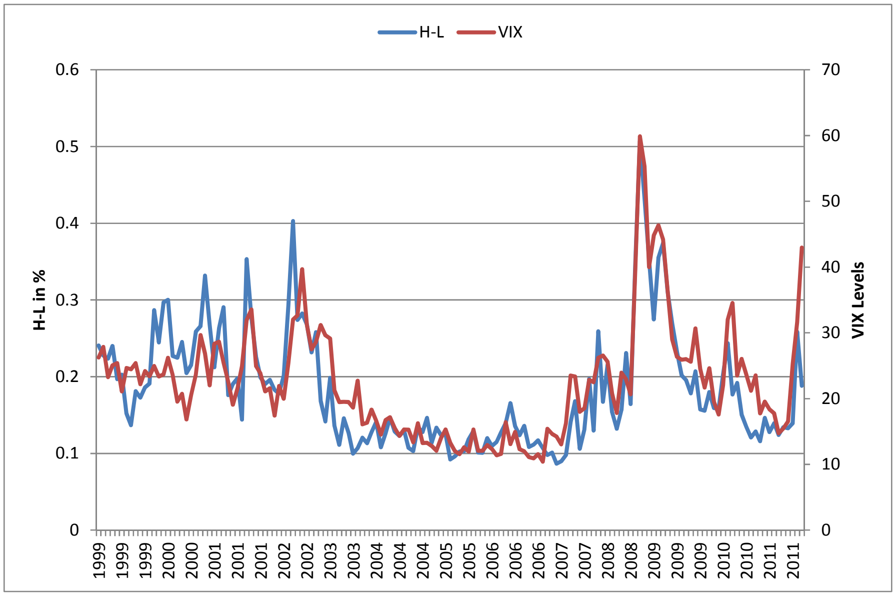
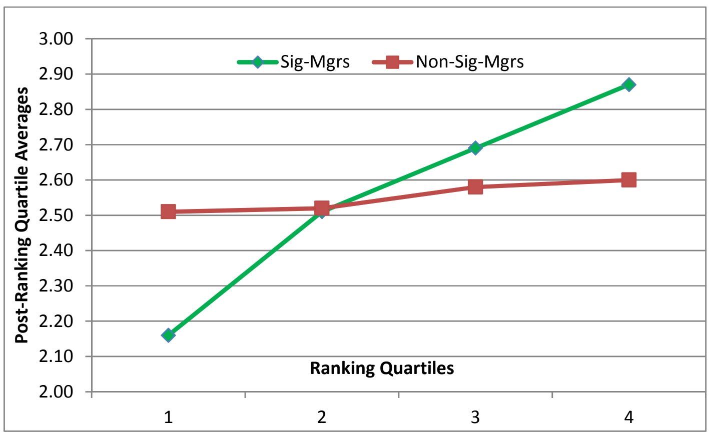


Figure 2 – Out-Of-Sample Quartile Ranking

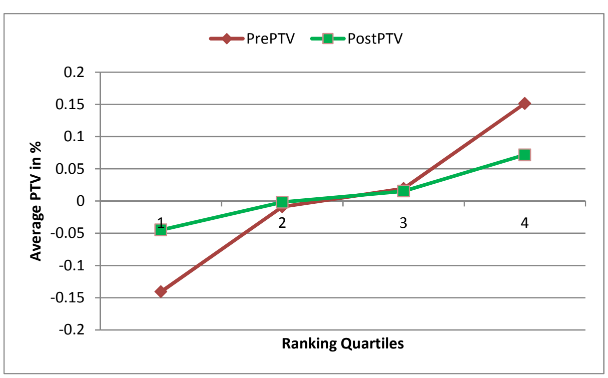
The figure depicts results from out-of-sample ranking from January 1999 to September 2011, a total of 153 months. Our bunched trades sample and the monthly *PTV* measure are defined in Table 2. Specifically we use a rolling window of 12 calendar months - the *Ranking-Window m-12* to *m-1* - to calculate the significance level of the difference between the top and bottom clients for each manager. We then define the significant managers during the rolling period as the top 10% *p*-value levels which correspond to simulated *p*-values at the 5% level. We term these managers the "Significant Managers". Using this information we rank each manager's clients into quartiles based on their *Ranking-Window PTV* averages. We then re-rank the clients into quartiles during month *m* based on month *m's* PTV averages (*Post-Rankin-Quartiles*). Graph A plots the *Post-Ranking-Quartile* averages based on the *Ranking* quartiles. We then calculate the *Post-Ranking* quartile averages based on the *Pre-Ranking* quartiles. *Sig-Mgrs* (*Non-Sig-Mgrs*) refers to the significant (non-significant) managers. Graph B plots the *Ranking* and *Post-Ranking* associated *PTV* averages, where graph B.1 (B.2) plots the averages of the non-significant (significant) managers. In each graph, *RankPTV* (*PostPTV*) is the *Ranking-Window's* (*Post-Ranking's) PTV* averages.

Graph A – Post Ranking Averages Based on Pre-Ranking Quartiles



Graph B –Average *PTV* Based on Pre-Ranking Quartiles

B.1 Significant Managers



B.2 Non-Significant Managers

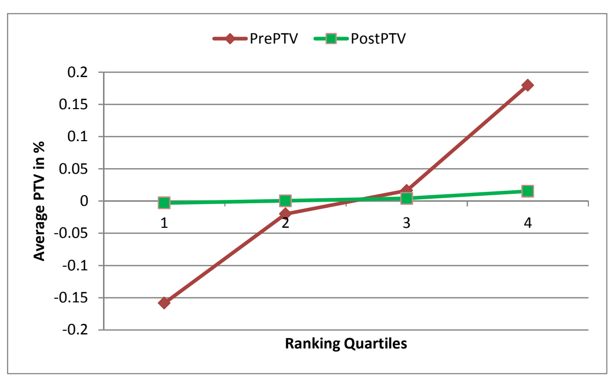
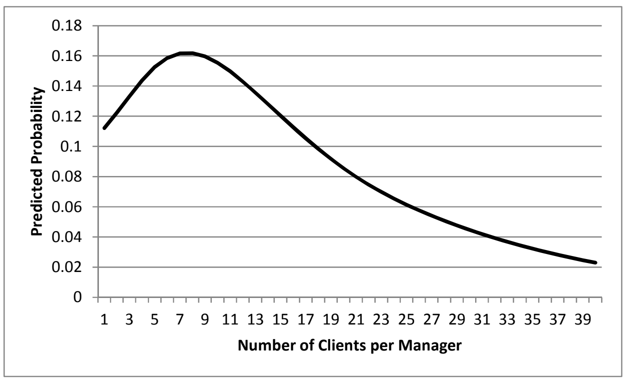


Figure 3 – Predicted Probabilities of the Significant Managers and Significant Clients

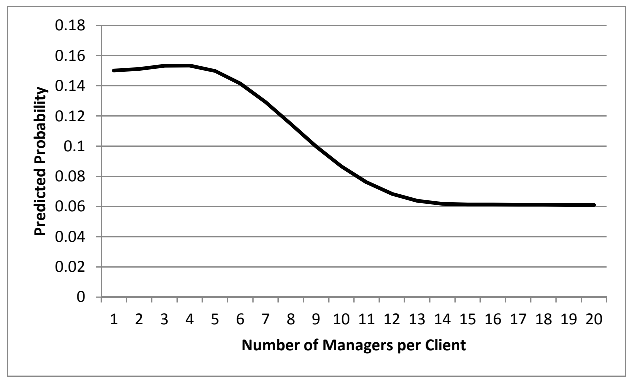
The figure depicts predicted probabilities from Table 7's and 8's Probit model estimations. Graph A depicts the predicted probabilities of being in the significant manager group based on the number of clients per manager (A.1) and number of managers per client (A.2) using Table 7 Specification 5. Specifically, we set the control variables to their means and vary our variable of interest based on the sample range. For example, the average min and max of the number of clients per manager are 1 and 40, respectively. In a similar manner, the average min and max of the number of managers per client are 1 and 20, respectively. Graph B depicts the predicted probabilities of being a significant positive client (B.1) or a significant negative client (B.2), based on the number of managers per client, using Table 8 Specifications 5 and 10. As in Graph A, we set the control variables to their means and vary our variable of interest based on the sample range.

Graph A – Predicted Probabilities of being in the Significant Manager Group

A.1 Number of Clients per Manager

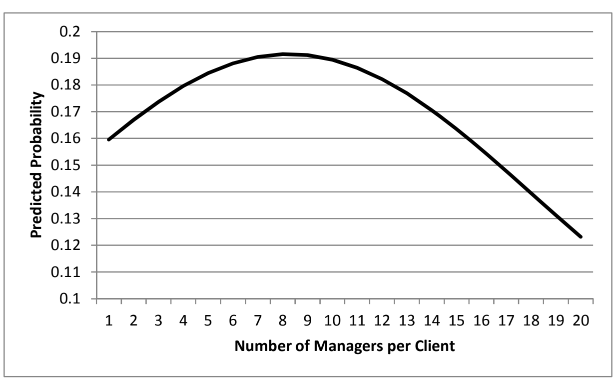


A.2 Number of Managers per Client



Graph B – Predicted Probabilities of being a Significant Positive or Significant Negative Client

B.1 Positive Clients



B.2 Negative Clients

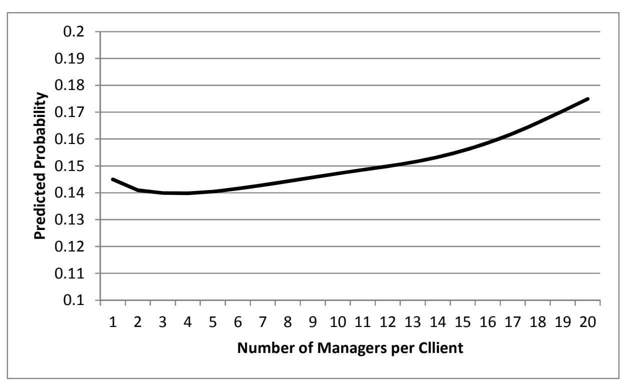
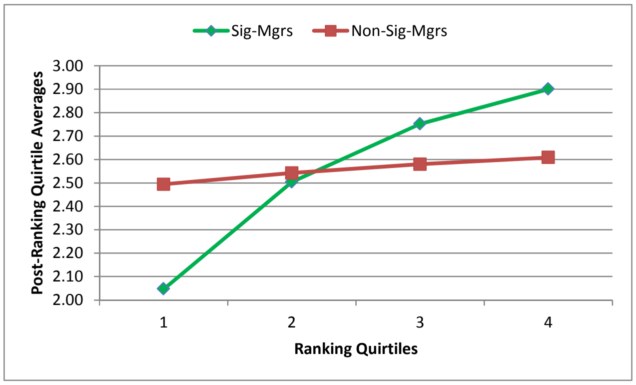


Figure 4 – Out-Of-Sample Quartile Ranking – the Sub-Sample of Same Broker Trades

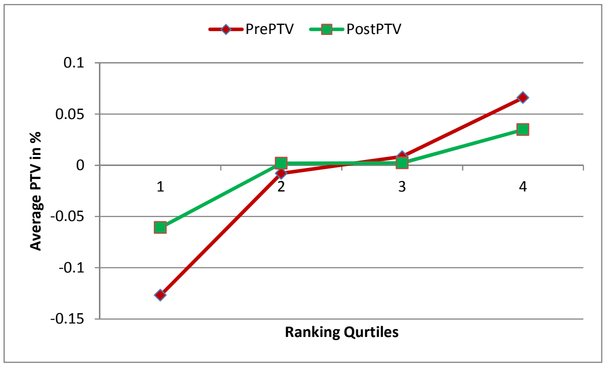
The figure repeats Figure 2's analysis for the sub-sample of trades that were executed by the same brokerage firm trades. To be in the sub-sample of same broker trades, a trade must be made by the same management company, for more than one client, in the same stock, on the same day, in the same direction (i.e., buy or sell), with different prices and executed by the same brokerage firm. This restriction reduces the sample of trades from 6,125,606 to 2,478,678 Mgr-Cnt-Stock-Day trades. As in Figure 2 we use a rolling window of 12 calendar months - the *Ranking-Window m-12* to *m-1* - to calculate the significance level of the difference between the top and bottom clients for each manager. We then define the significant managers during the rolling period as the top 10% *p*-value levels that correspond to simulated *p*-values at the 5% level. We term these managers the "Significant Managers". Using this information we rank each manager's clients into quartiles based on their *Ranking-Window PTV* averages. We then re-rank the clients into quartiles during month *m* based on month *m's* PTV averages (*Post-Rankin-Quartiles*). Graph A plots the *Post-Ranking-Quartile* averages based on the *Ranking* quartiles. We then calculate the *Post-Ranking* quartile averages based on the *Pre-Ranking* quartiles. *Sig-Mgrs* (*Non-Sig-Mgrs*) refers to the significant (non-significant) managers. Graph B plots the *Ranking* and *Post-Ranking* associated *PTV* averages, where graph B.1 (B.2) plots the averages of the non-significant (significant) managers. In each graph, *RankPTV* (*PostPTV*) is the *Ranking-Window's* (*Post-Ranking's) PTV* averages.

Graph A – Post Ranking Averages Based on Pre-Ranking Quartiles



Graph B –Average *PTV* Based on Pre-Ranking Quartiles

B.1 Significant Managers



B.2 Non-Significant Managers