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 for strategic performance allocation. Focusing our attention to a subsample of bunched trades – trades on the same day, stock and direction for more than one client - we find that some clients receive systematically better prices than others; where the magnitude can be as large as 0.50% per trade volume. Analysis within management companies reveals strong evidence for persistence in price allocation. Finally, we explore the characteristics of management companies who might engage in price allocation and the clients likely to be involved. To the best of our knowledge this paper is the first to use actual trading data to investigate channels for strategic performance allocation.

1 Introduction

Investment management companies have inherent principle-agents conflicts. First, maximizing the value of the management company as a whole may be different than maximizing the value of its individual clients. Second, management companies may have a diversified set of clients such as mutual funds, corporate pension and profit-sharing plans, and high net worth individuals, which may lead them to treat different clients differently.[1] Recognizing these conflicts, a new line of research on strategic performance allocation (hereafter, "SPA") has become popular during recent years.[2] For example, Gasper, Massa and Matos (2006) (hereafter, "GMM") provide evidence for cross-fund subsidization between funds within a mutual fund family may increase the total profits of the fund family. Chaudhuri, Ivkovic and Trzcinka (2013) (hereafter, "CIT") find evidence for SPA in the pension product industry. These papers present compelling results. However, because they use periodic returns to detect SPA, a smoking gun is arguably needed.

In this paper we provide such a smoking gun: direct evidence for SPA. We take advantage of fairly new proprietary database provided by Ancerno Ltd, which includes trades of delegated investment advisers (management companies at the 13F level) on behalf of their clients. We use this structure to explore the channel of strategic price allocation among "bunched

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[1] Examples for papers which recognized such conflicts are: Massa (2003), Nanda, Wang, and Zheng (2004), Gasper, Massa and Matos (2006), Guedj and Papastaikoudi (2008), Bhattacharya, Lee and Pool (2012), Chaudhuri, Ivkovic and Trzcinka (2013), and Goncalves-Pinto and Schmidt (2013).

[2] Conflicts at the management company level are different than conflict at the fund manager level. Evidence for conflicts at the fund manager 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., Lakonishock, Shleifer, Thaler, and Vishny (1991) and Carhart, Kaniel, Musto and Reed (2002)) and late trading (Chalmers, Edelen and Kadlec (2001)), and Gastineau (2004)).

trades."[3] We find that a statistically significant fraction of managers favor specific clients when allocating bunched trade prices. We find that the average magnitude of this price allocation is economically significant. We then analyze the characteristics of the managers and clients likely to be involved.

Delegated portfolio managers have incentives to aggregate (bunch) trades. Bunching trades may lead to smaller transaction costs or commissions, and may reduce administrative costs. One example can be found in one of the management company ADV's filing:

"Where X buys or sells the same security for two or more clients, X may place concurrent orders with a single broker, to be executed together as a single "block" in order to facilitate orderly and efficient execution."… "Clients who may want to direct the firm to use a particular broker should understand that this might prevent X from aggregating orders with other clients or from effectively negotiating brokerage compensation on their behalf."

Consistent with these statements, when examining clients' trades within the same management company, we find that about 50% of the typical monthly volume of trades in the Ancerno database is made up by bunched trades. Interestingly, only one-fourth of the bunched trades are allocated to clients using similar prices. Since managers typically have several hours after orders are filled to allocate the shares to clients, there is ample opportunity for such strategic behavior.

Ancerno covers a diversified set of clients which include pension sponsors together with other money managers. Each management company has multiple clients. Interestingly there are also multiple links from clients to management companies (this is common in the pension fund

[3] Bunched trades are trades which are aggregated together across clients by the management company for trading purposes.

industry).[4] We take advantage of this structure to explore the channel of strategic price allocation. In particular we are interested in learning 1) whether some clients receive systematically better prices than others, 2) whether there are systematic differences between clients within management companies, 3) the determinants of management companies that might be engage in SPA, 4) the determinants of clients who receive better or worse prices than others, 5) the determinants of observing bunched trades with different prices.

Our approach is simple. We focus on the sub-sample of bunched trades on a given day across clients within a management company. Specifically, we require each bunched unit to be in the same stock, on the same day, in same direction (i.e., buy or sell) with different prices. For each client we calculate a profit measure which captures the difference between his trade price and the value weighted price across all clients (i.e., a hypothetical equal allocation price). Using these price differences we calculate for each client its profit-to-trade volume measure (hereafter, PTV) based on the client's volume for the bunched trade. We start with the client-manager pairs. For each client-manager pair we calculate the sample's *PTV* average. We find double the amount of significant averages than what one would except to find under a random allocation benchmark.[5] The ballpark economic magnitude *PTV* is between 0.10% to 0.50% per trading volume, depending on the client age and type of trades.

We next explore the differences between clients within a given management company. Again, we find that the number of management companies with statistically significant differences, is between two to three times the amount one would expect to find under a random

[4] Example for studies which investigated 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).

[5] We simulate 10,000 random samples by reshuffling the clients in each Manager-Date-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.

allocation benchmark. Using these differences, we split our managers into significant and non-significant groups. Strikingly, we find strong evidence for 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. We apply parametric and non-parametric tests such as portfolio ranking and cross-sectional Fama-MacBeth regressions. Importantly, our result is robust to the various tests applied.

Having established the existence of price allocation among sub-group of portfolio managers, we next explore the characteristics of the significant managers. Utilizing Fama-MacBeth Probit models to estimate the probability of being in the significant group, we find that managers whose clients hold similar stock 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 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 be in the significant group. On the other hand, clients whose portfolios overlap with more clients under the same manager, and who have volatile and poor performing stocks in their portfolios, are more likely to be in the significant group. In addition, having a fewer total managers increases the likelihood of being favored.

In our final set of tests we examine the probability of observing a bunched trade with different prices. We combine our sample with the sample of bunched trades with the same prices. We find that the probability of observing a bunched trade with different prices increases with the number of clients sharing trades, the number of intraday trades needed to execute the transactions and the volume per shared trade.

Our results contribute to the literature on strategic performance allocation, and conflicts in management companies in general, by providing direct evidence (i.e., a smoking gun) of price allocation. Furthermore, we shed light on the types of managers and clients likely to be involved in such activities.

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. We conclude in Section 5.

2 Trading Environment, Data and Summary statistics

2.1 Trading Environment

Management companies typically 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 their clients' portfolios typically overlap with each other, management companies may find it convenient to aggregate (or bunch) similar trades across clients for cost saving reasons. These trades may be processed with a single broker and executed together as a single "block" in order to facilitate orderly and efficient execution. The manager typically submits an order to the brokerage company specifying the total amount of shared needed on a given day. If the trade is big, or if prices are volatile (as may be the case with small or illiquid stock) the overall trade may be executed with different prices.

After executing a bunched trade, management companies allocate the different trade prices across clients. A company may choose to equally allocate the trade price across clients (using the value weighted price of the entire trade) but may also choose other options such as an allocation based on the price impact, using a pre-determined random order, or based on any other objectives for specific 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) which is a widely recognized consulting firm that provides consulting services to institutional investors which help them monitor their trading costs.[6] Ancerno's database includes trades for three types of clients (defined by Ancerno for their own purpose): Client Type 1 for pension plan sponsors; Client Type 2 for money managers; and Client Type 3 for Brokers. Some examples of Ancerno's clients are: CalPERS, the Commonwealth of Virginia, and the YMCA retirement fund pension plan sponsors; and Massachusetts Financial Services (MFS), Putman Investments, and Lazard Asset Management money managers.

As mentioned by Puckett and Yan (2011) (hereafter, "PY") and Franzoni and Plazzi (2013) (hereafter, "FP"), Ancerno's data have a few appealing features for academic research. First,

[6] Previous studies that use Ancerno data include: Chemmanur, He, and Hu (2009), Goldstein et al. (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand, Irvine, Puckett and Venkataraman (2012), Jame (2012), Busse, Green, and Jegadeesh (2012), Franzonni and Plazzi (2013), and Gantchev and Jotikasthira (2013).

because Ancerno's data are released in monthly batches, survivorship bias is not likely to be an issue. These batches are not updated, and as a result the data includes institutions that are no longer exists at the end of the sample. Given that the purpose of the 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. Moreover, the data include the complete records of each client since becoming Ancerno's client. 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 and conclude that although Ancerno data capture the activities of a subset of pension and money managers, the subset 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 help us link clients to their management companies. These links are crucial to our study since we explore the management company trades across clients. Our data include the following identification codes: *Clientcode,* a numerical code given to any Ancerno's client. These codes are unique and the identity of the clients is not revealed; *Clienttype,* based on Ancerno's internal classification. These codes classify clients as pension plan sponsors, money managers, and brokers; *Managercode*, a unique numerical code given to the management company, together with the variable *Manager,* which provides the names of the management companies. We are able to match the management companies' names to the 13F files and verify that these are the management companies are at the 13F level. The last identification variable is *Clientmgrcode* which Ancerno assigns 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 break out their relation to a manager into several categories. Our analysis does not require this variable, since we bunch trades at the management company level.

Our main data 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 if a trade is a buy (1) or a sell trade (-1). A detailed explanation about Ancerno variables can be found in 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 trade" at the daily level, by calculating the total number of shares and value-weighted price. 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 transaction used and use that variable as control.

As mentioned, our objective is to investigate how bunched trade prices are allocated across clients sharing the same trade. Appendix A provides an example of a bunched trade made by a management companies on behalf of its clients. In this example, a 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. As in Appendix A, the trade must be in the same stock on the same date in the same direction (i.e., buy or sell) with different execution prices. 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. Multiple links are observed when the client is of type 1 (i.e., a sponsor plan or a pension plan), since a pension fund's total portfolio may be managed by multiple money managers. As for type 2 clients, with a few exceptions, the majority result in a one to one match.

We match our sample to CRSP using both stock's ticker and *CUSIP*. To make sure that 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 seems to have significant changes in its time-series links to the management company codes in the middle of the sample. After applying these filters, our initial data contains 39,597,396 Manager-Client-Date-Stock trades which are executed via 204,944,704 partial trades. Recall, that to be in our sample, we require managers to have more than one client. As a result, we exclude managers that are linked with only one client. From the sample of 39,597,396 Manager-Client-Stock-Date trades, we are left with 6,125,606 Manager-Client-Stock-Date trades which translates to 1,938,525 Manager-Stock-Date bunched trades. Based on these numbers, the average number of clients in a bunched trade is 3.21. Importantly, although these trades account for around 16% of the observations (i.e., 39 million vs. 6 million), the average volume processes is around 50% (25%) of the equally (value) weighted clients' total monthly volume. The trades are executed via 488 different management companies and 825 different clients, which translates to 5,144 different Manager-Clients pairs.

2.3 Profit-to-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 equal price allocation (hereafter, "EPA"), each client should receive the same value-weighted price. We calculate that price by dividing the total shared $ volume of all clients to total number of shares bought or sold. Using the EPA, we compute each client's hypothetical profit or loss as the difference between its actual price and the equal allocation price. We then construct the Profit-to-Trade-Volume (hereafter, *PTV*). Specifically, we define *PTV* as:

[# of shares * (Actual Price – EPA) / ($ Volume)]* SignOfTrade*(-1) (1)

Note that the profit component, [# of shares * (Actual Price – EPA)], 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 variable 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 shared transaction 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 average overlap ratio is 83, 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., shared and non-shared) and does not take volume into account. In a similar manner, the ratio of monthly shared trade volume to the client's monthly **total volume** is 50%. If we account for volume, and calculate the volume-weighted average across clients, the ratio drops to 25%. This indicates that high volume clients have lower ratios. Considering the client's age, the average number of shared-trade months of a client-manager pair is 27 months. The average number of months considering all trades (shared and non-shared) is 34 months.

As for the daily-based variables, 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 the 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

In this section we examine whether some managers systematically allocate better/worse prices across clients. 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.[7] We begin our investigation by calculating the client-manager sample *PTV* averages and their statistical significance. We then explore differences in clients' PTVs within management companies and examine statistical significance. Finally, we explore the out-of-sample persistence of these differences. To account for the appropriate random allocation benchmark, we simulate random samples and use their distributions in our tests.[8]

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 equal price allocation, we simulate 10,000 random samples by reshuffling the clients in each manager-Date-Stock bunched trade (see Appendix A for an example of such a trade). Randomly reshuffling at

[7] Transaction-weighted monthly average yields similar results.

[8] Other examples of papers using simulated benchmarks are: Kosowski, Timmerman, Wermers and White (2006), and Fama and French (2010).

the Manager-Date-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 that 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.

Splitting the sample into positive and negative averages reveals that 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. This, in turn suggests that the burden of price allocation is shared with more clients, thus there are lower number of 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.

Table 3 presents the economic magnitude of Table 2's significant clients' *PTV*s at the 10% *p*-value cutoffs for different frequencies. 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 positive to negative is stable is around 1.4 on average. 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% afterwards to 0.06% (0.15%) on average. 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).

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-Date-Stock bunched trade (see Appendix A for an example of such a 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* 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 rolling 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). 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 test with cross-sectional regressions including manager fixed effects yields similar results. Because these are truly out-of-sample tests, these results as 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 a non-parametric out of sample test. Using the rolling windows 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's* (*Post-Ranking's) 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 an evidence of reversal in the non-significant manager group. 5 out of 6 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%.

4. Determinants of significant Managers and Clients

Having established the existence of strategic price allocation, this section examines the determinants of those managers likely to engage in price allocation, and the determinants of the clients being favored, and those bearing the costs. Since the identities of the clients are not disclosed by Ancerno, we are only able to use variables constructed from trading data.

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 a monthly cross-sectional Probit model, and calculate the time-series average of the model's estimates. The models are estimated at the manager level with 24,902 Manager-Year-Month observations. 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. In a similar manner, 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 univariate analysis. Panel B indicates that the selection order of the explanatory variable doesn't affect the estimated coefficients. As a result, we'll 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 manner, 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 summarize, we find that 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 manager-client pairs. The significant levels are based on Table 2's *p*-value cutoffs. Specifically, our dependent variable is set to be 1 if a client-manager pair is in the significant managers 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 a monthly cross-sectional Probit model, and calculate the time series average of the model estimates. The models are estimated at the Client-Manager-Year-Month level.

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), the monthly returns standard deviation (SD), the accumulated return over the previous 1-6 and 7-12 months (MOM16 and MOM712, respectively), 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. Based on the individual stock's characteristics, we then calculate the trade-weighted average, for each month and client-manager pair. All stock characteristics are calculated at the end of month *m*-1.

Specifications (1)-(5) and (6)-(10) 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. This makes sense, since a major client's price should converge to the value-weighted 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. 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. In a similar manner, the number of managers per client is positive and significant for the positive clients and not significant for the negative clients.

Exploring the effect of size, liquidity and volatility, Specification (2) indicates that clients that trade in small and illiquid stocks are more likely to be significant in both directions. This makes sense since small and illiquid stocks tend to have bigger price differences which should lead to more opportunities for price allocation. Interestingly, Specification (3) indicates that standard deviation is the main driver behind size and liquidity, which is consistent with Figure (1). Specifications (7) and (8) present similar results, although the sign of size seems to be in the opposite direction. Comparing Specifications (4) and (9) indicates that the price allocation may be a subsidy for poor previous performance. The variables Mom16 and Mom712 load negatively for the positive clients, indicating that the probability of being a positive significant client increases with poor performance during previous period. Contrary to the results found for the positive clients, these variables are not significant for the negative clients. We recognize that a perfect measure would be the actual gain and losses from pervious trades. Nevertheless the differences between the positive and negative clients are notable. Finally, book-to-market has a positive effect for the positive clients and no effect on the negative clients, and beta doesn't seem to have an effect on both types of clients.

To summarize, we find that 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 volatile and poor performing stocks are more likely to be the beneficiaries of price allocation.

4.3 The Probability of Observing Different Prices

So 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 value-weighted price (i.e., an equal allocation 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 value-weighted 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 shared trades with ***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 date, 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-Date-Stock trades which are executed via 10,823,232 partial trades. The Manager-Client-Stock-Date trades are bunched into 1,651,801 Manager-Stock-Date 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-Date-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 presents 5 different specifications used to estimate these probabilities. Specification (1) is at the manager-bunched transaction level; Specification (2) is at the Manager-Year-Month level; Specifications (3) and (4) are at the Manager-Client-Year-Month level with and without Manager fixed effects; and Specification (5) runs a 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. Conclusion

In their ADV filings, management companies often state that in the case that two or more of their clients buys or sells the same security, the company will aggregate (bunch) the orders and executed them as a single "block." 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 similar trades between their clients.

Using a new measure which captures the client's losses or gains from a given bunched trade, we find clear evidence indicating that different client systematically get different prices. The gains and losses can be as large as 0.50% per trade 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 determinants of management companies which might be engage in price allocations, and the determinants of clients with significant gains and losses.

Our results support Gasper, Massa and Matos (2006) and Chaudhuri, Ivkovic and Trzcinka (2013), by providing direct evidence through trades (i.e., a smoking gun) for strategic performance allocation. 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- Shared Trades with Different Prices

Appendix A, presents an example of a shared trade made by a management companies on behalf of its clients. To be in our shared 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 date, in the same direction (i.e., buy or sell) with different prices. We tem 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. *$Vol*, is the dollar volume of trade. *PRC* is the price associated with each client's trade. *Equal Allocation Price* is a hypothetical price in the scenario where the management company allocates the same price to all clients sharing the trade; calculated as the sum of all clients' *$VOL* divided by the sum of all shares bought or sold (i.e., value weighted average price).

Manager	DATE	Stock	Client	Num TRD	Num SHR	$ VOL	PRC
MGR1	1/1/2010	S1	C1	1	500	23,510	47.02
MGR1	1/1/2010	S1	C2	1	500	23,530	47.06
MGR1	1/1/2010	S1	C3	1	500	23,530	47.06
MGR1	1/1/2010	S1	C4	1	1,000	47,080	47.08
MGR1	1/1/2010	S1	C5	2	2,000	94,120	47.06
Equal Price Allocation					4,500	211,770	47.06

Appendix B – Variable Definition

Appendix B reports and defines the variables used in the paper's analysis. *BASE* is the base of the variable calculation. For example, *Client-Per-Manager* is calculated for each year and month at the manager level (*Y-M-Mgr*). *Cnt-Trd-Relative-Vol* is calculated for each stock and date, at the Client-Manager level *(Mgr-Cnt-Date-Stock*).

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	
Y-M	Year-Month	
Y-M-Mgr-Cnt	Year-Month-Manager-Client	
Mgr-Cnt-Date-Stock	Manager-Client-Date-Stock	
	Number of different stocks shared per client-manager Pair	
Monthly variables		
Cnt-Per-Mgr	Number of clients per manager	Y-M-Mgr
Mgr-Per-Cnt	Number of managers per client	Y-M-Cnt
Num-Trd-In-Mon	Number of the monthly shared transactions per client-manager Pair	Y-M-Mgr-Cnt
Diff-Stocks-Shared-In-Month	Number of different stocks shared per client-manager Pair	Y-M-Mgr-Cnt
Mgr-Cnt-Shrd-Vol	Client-manager pair's monthly shared $ volume	Y-M-Mgr-Cnt
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	Y-M-Mgr-Cnt
Num-FF48-Ind	Average number of different industries per client, based on Fama-French's 48 industry classification codes	
SDDP-Vol-to-Total-Vol	Monthly shared SDDP volume to Total Trade volume ratio	Y-M-Mgr-Cnt
Months with Shared Trades	Number of months with SDDP trades	Y-M-Mgr-Cnt
Months with All Trades	Number of months with trading activity	Y-M-Mgr-Cnt
Months with Shared to All Trade Ratio	Months with SDDP trades to months with All trades ratio	Y-M-Mgr-Cnt
Daily 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 variables		
Size	Size in $ millions, calculated as the number of outstanding shares times the end of month price	Y-M-Mgr-Cnt
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	Y-M-Mgr-Cnt
SD	Standard deviation of monthly returns, calculated for each month based on a rolling window of 24-36 months	Y-M-Mgr-Cnt
MOM16	Accumulated return of the previous 6 months	Y-M-Mgr-Cnt
MOM712	Accumulated return of the previous 7-12 months	Y-M-Mgr-Cnt
BM-Ind-Adj	Industry adjusted Book-to-Market ratio as suggested by Cohen and Polk (1998) and Wermers (2004)	Y-M-Mgr-Cnt
Beta	Beta from the market model based on 24-36 months	Y-M-Mgr-Cnt

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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 shared 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 date, 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 shared 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 shared 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 equal price allocation, calculated by dividing the total shared $ volume of all clients to 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 Variables* (*Daily 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 Variables					
Cnt-Per-Mgr	5.16	3.47	4.83	25,860	Y-M-Mgr
Mgr-Per-Cnt	3.45	2.69	2.97	38,770	Y-M-Cnt
Num-Trd-In-Mon	46.50	19.81	83.81	135,112	Y-M-Mgr-Cnt
Diff-Stocks-Shared-In-Month	21.25	10.66	36.04	135,112	Y-M-Mgr-Cnt
Overlap-Ratio	83.84	100.00	27.06	135,112	Y-M-Mgr-Cnt
Overlap-Ratio - VW	42.01	35.24	N/A	135,112	Y-M-Mgr-Cnt
SDDP-Vol-to-Total-Vol	53.50	56.85	32.48	135,112	Y-M-Mgr-Cnt
SDDP-Vol-to-Total-Vol - VW	25.52	21.14	N/A	135,112	Y-M-Mgr-Cnt
Num-FF48-Ind	29.17	33.64	11.98	135,112	Y-M-Mgr-Cnt
Num-FF48-Ind-VW	31.21	33.93	N/A	135,112	Y-M-Mgr-Cnt
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 Variables					
Num-Cnt-Sharing-Trade	3.21	2.45	2.23	1,938,525	Mgr-Date-Stock
Num-Partial-Trds-By-Cnt	5.65	1.07	15.95	6,125,606	Mgr-Cnt-Date-Stock
Vol-Per-Cnt-Trade	571,050	76,750	1,637,927	6,125,606	Mgr-Cnt-Date-Stock
AbsPTV	0.08	0.00	0.33	6,125,606	Mgr-Cnt-Date-Stock

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. To be in our shared 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 date, 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 shared 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 shared 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 equal price allocation, calculated by dividing the total shared $ volume of all clients to 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 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 equal price allocation, we simulate 10,000 random samples by reshuffling the clients in each manager-Date-Stock bunched trade (see Appendix A for such a trade). Using the Manager-Date-Stock unit, accounts for the type of stock, 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 manager-client 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) manager-client to negative (negative and significant) manager-client 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% significant level. Our shared 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 10th and 90th 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 shared trades above the monthly H-L cross-sectional average. The *H-L* in turn, is the shared 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 difference between their client *PTV* averages for different *p*-value levels and client frequencies. Our shared 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 difference using a standard *t*-test. *Min-Month-Freq* is minimum number of monthly client-manager sample observations required to be included in the sample. *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 equal price allocation, we simulate 10,000 random samples by reshuffling the clients in each manager-Date-Stock bunched trade (see Appendix A for such a trade). Using the Manager-Date-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 difference and store that 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 shared 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. 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 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 shared trades sample and the monthly *PTV* measure are defined in Table 2. Specifically, for each manager we divide 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 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 for reference). Using this information we calculate the averages and differences between the top and bottom clients during their *Post-Ranking* period. *Min-Month-Freq* is minimum number of monthly client-manager sample observations required to be included in the sample. *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 shared 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. 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 for reference). 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, *LnCntPerMgr* is the natural log of *CntPerMgr*, and *CnrPerMgr2* is *CntPerMgr* squared. For each month of the 153 months we run a manager level Probit model. *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 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 shared 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 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 for reference). 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, *LnMgrPerCnt* is the natural log of *MgrPerCnt*, and *MgrPerCnt2* is *MgrPerCnt* squared. For each month of the 153 months we run a client-manager level Probit model. *SMP* is the number of client-manager observations used 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 Newey-West (1987) correction.

	Positive					Negative				
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
LnCnt-Trd-Relative-Vol	-0.078	-0.122	-0.115	-0.121	-0.129	-0.131	-0.150	-0.160	-0.201	-0.406
	2.81	3.60	3.49	3.60	3.46	3.35	3.16	3.05	3.08	2.52
LnMgr-Cnt-Shrd-Vol	0.125	0.162	0.156	0.166	0.174	0.080	0.096	0.110	0.143	0.252
	8.46	8.51	8.63	9.02	8.30	4.79	4.42	4.77	4.51	2.73
LnOverlap-Ratio	0.337	0.363	0.382	0.393	0.460	0.018	0.046	0.085	0.096	0.192
	2.45	2.59	2.81	3.00	2.85	0.22	0.55	1.07	1.08	1.44
Mgr-Per-Cnt	0.075	0.071	0.069	0.076	0.076	0.015	0.004	-0.002	0.013	0.029
	4.26	3.96	3.87	4.27	3.86	0.76	0.21	0.08	0.38	0.78
Mgr-Per-Cnt2	-0.005	-0.005	-0.005	-0.005	-0.005	0.000	0.000	0.000	0.000	-0.002
	5.25	4.85	4.72	5.15	4.80	0.22	0.17	0.42	0.04	0.91
LnSize		-0.057	-0.009	-0.014	0.016		0.134	0.211	0.259	0.550
		2.85	0.31	0.46	0.47		3.82	5.55	4.85	3.01
HBAS		2.690	1.965	1.510	0.950		10.294	9.930	19.499	37.487
		2.07	1.48	0.94	0.61		3.80	3.29	2.27	2.08
SD			4.885	6.172	10.760			7.301	5.342	29.323
			3.59	3.72	3.80			2.94	0.91	1.13
MOM16				-0.910	-1.227				2.843	0.329
				3.35	3.74				1.14	0.11
MOM712				-0.473	-0.688				-1.893	-0.953
				2.06	2.32				1.14	0.56
LnBM-Ind-Adj					0.168					0.565
					1.95					0.65
Beta					-0.216					-1.340
					1.24					0.77
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 Shared Trades with Different Prices

The Table reports the probability of engaging in shared trades with different prices using Fama-Macbeth (1973) Probit models. The dependent variable receives the value of 1 if the shared transaction is with different prices and 0 otherwise. ***For this test only*** we combine our main *SDDP* sample with a second sample of shared trades with ***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 date, in the same direction (i.e., buy or sell) with ***same price***. We term this sample *SDSP*, which stands for same-direction-same-price. Our shared 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-Shared Transaction level; Specification (2) is at the Manager-Year-Month level; Specifications (3) and (4) are at the Manager-Client-Year-Month level with and without Manager fixed effects; and Specification (5) runs a Manager-by-Manager cross-sectional regressions for each year and month. *SMP* is the number of observations used the regressions. In all specifications, the *t*-statistics are adjusted for serial correlation using 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	Y-M-Mgr-Cnt
Monthly Variables					
Cnt-Per-Mgr	4.63	3.05	4.01	23,568	Y-M-Mgr
Mgr-Per-Cnt	3.03	2.29	2.58	36,072	Y-M-Cnt
Num-Trd-In-Mon	33.31	7.81	132.17	110,503	Y-M-Mgr-Cnt
Diff-Stocks-Shared-In-Month	15.92	5.55	38.35	110,503	Y-M-Mgr-Cnt
Daily Variables					
Num-Cnt-Sharing-Trade	2.38	2.00	0.96	1,651,801	Mgr-Date-Stock
Num-Partial-Trds-By-Cnt	2.64	1.02	5.19	3,804,319	Mgr-Cnt-Date-Stock
Vol-Per-Cnt-Trade	290,862	49,705	764,586	3,804,319	Mgr-Cnt-Date-Stock

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-Y-M	Mgr-Cnt-Y-M	Mgr-Cnt-Y-M	Mgr-Trns
SMP	3,588,200	49,352	245,613	245,613	3,588,200
N	153	153	153	153	98,747 - 153

Figure 1 – Time series of Shared 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 shared transaction's high to low price divided by the average price, presented in %. The definition of our shared sample and the monthly PTV measure calculation are as defined in Table 2.

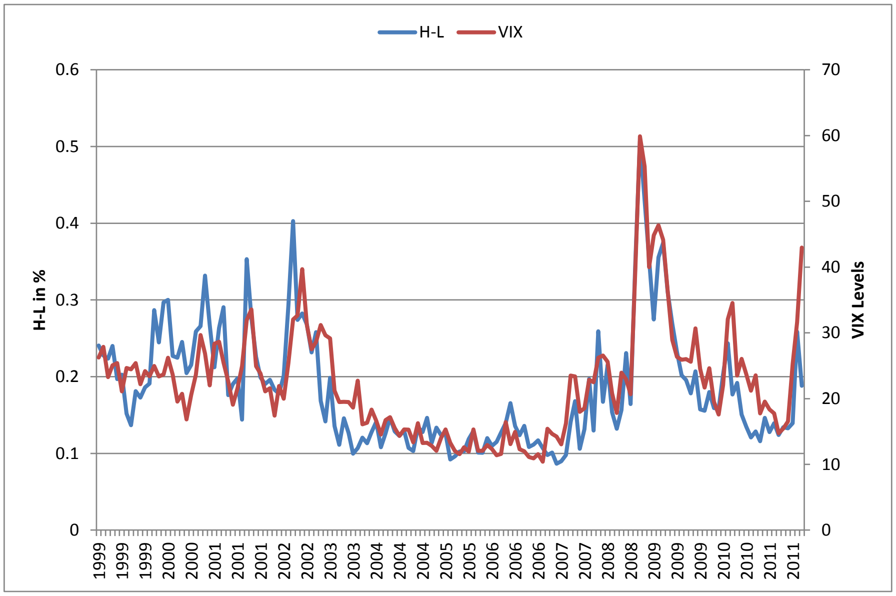
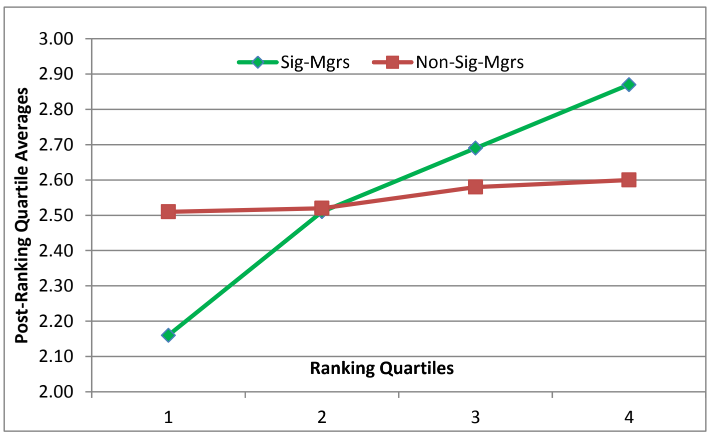


Figure 2 – Out-Of-Sample Quartile Ranking

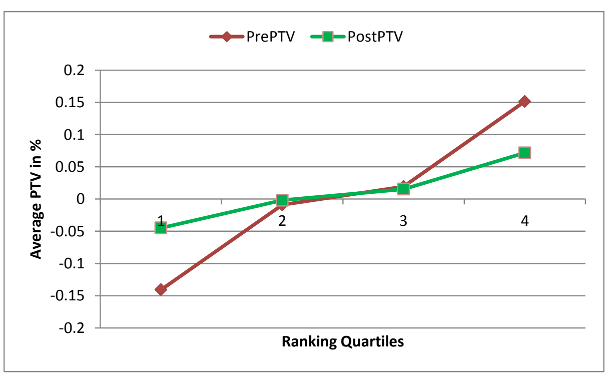
The Figure depicts results from out-of-sample ranking from January 1999 to September 2011, a total of 153 months. Our shared trades sample and the monthly *PTV* measure are defined in Table 2. Specifically we use a rolling window of 12 calendar months - the *Ranking-Window m-12* to *m-1* - to calculate 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