# Splitting and Shuffling: Institutional Trading Motives and Order Submissions Across Brokers *

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**Abstract**

This paper studies order submission strategies by institutional investors when trading on private information. By merging institutional daily transactions with original/confidential 13F filings, I separate informed trades from uninformed ones. Informed large orders tend to be split across more brokers and over more days. While same brokers tend to work uninformed large orders over multiple days, the brokers who facilitated early parts of broken-up informed orders rarely receive the remaining parts of the same orders on later days. Institutional investors also provide camouflage for their informed orders by mixing an informed order with other uninformed orders simultaneously sent to the same broker. As a result, a higher degree of shuffling a portfolio of orders is associated with a larger share of informed trading volume. The splitting and shuffling strategies designed to conceal informed trades from brokers and other market participants tend to lower institutional trading costs, especially on informed orders.



*Keywords: Institutional trading, informed trades, brokers, order submissions, trading costs*

# 1 Introduction

In this paper I study the order submission strategies of institutional investors when they trade on private information. Motivating the analysis is a substantial literature that models the strategies that informed traders can use to conceal their trading motives and moderate the price impact of their trades. Informed traders can, for instance, engage in dynamic strategies, optimally splitting orders over time to better hide their trades among those of uninformed noisy traders (e.g., Kyle (1985), Easley and O'Hara (1987)). Similarly, informed traders can seek opportunities and venues in which their trades can be better concealed (e.g., Admati and Pfleiderer (1988)). Since the presence of informed trading also raises the costs faced by uninformed traders, the uninformed traders have the incentive to certify (i.e., engage in sunshine trading) that their trades are not information-driven (see Admanti and Pfleiderer (1991)). Seppi (1990) suggests that uninformed traders can be screened and face lower costs trading blocks in the non-anonymous upstairs market; whereas informed traders would split up blocks into a series of smaller orders and trade downstairs anonymously. Consistent with the thrust of these models, this paper finds that informed institutional traders follow order submission strategies intended to obscure their trading motives.

Institutions trading on information face the supplementary risk that their trading will be recognized and mimicked by other traders. Several recent empirical papers have raised concerns about the private information being detected by other market participants such as high-frequency traders (HFTs) or being leaked through brokers to other investors. Korajczyk and Murphy (2019) find that high-frequency traders submit more same-direction orders during institutional trade executions. Using Swedish equity data, Van Kervel and Menkveld (2019) present evidence that HFTs supply liquidity at the beginning, but eventually trade in the same direction as the institutions submitting the original orders. These papers argue that such "back-running" is costly to institutional investors trading on private information. Di Maggio et al. (2019) highlight the brokers' role in facilitating back-running by showing that brokers can extrapolate large informed trades from order flows and selectively leak this information to their important clients. Recently, Yang and Zhu (Forthcoming) propose that informed traders can randomize their order flows to prevent other traders from back-running on their fundamental information.

There are several key findings in the paper regarding the order submission strategies of informed institutional investors. I find that institutional investors tend to spread out their orders across more brokers and over more days when they are trading on information. Institutional investors appear to randomize among brokers when submitting information-driven orders. Institutional investors not only shuffle their order flows across brokers, but also appear to submit their informed orders "camouflaged" among several other uninformed orders when submitting information-driven orders to a broker. Furthermore, this paper provides evidence that splitting and shuffling strategies, apparently designed to hide information from brokers and other investors, lead to lower trading costs as measured by implementation shortfall, especially on informed orders.

My empirical analysis requires separating informed trades from uninformed ones to analyze the order submission strategies of institutional investors trading on private information. Following Agarwal et al. (2013), I first identify "confidential" holdings by merging and comparing original 13F filings with the amendments to the original filings. 13F investors can request confidential treatment for certain holdings, which can be omitted in the original 13F filings and reported later in the amendment filings. Agarwal et al. (2013) show that confidential holdings of institutional investors (especially hedge funds) are information-motivated and tend to outperform the other holdings.[1] Next, I match the managers from the ANcerno institutional trading dataset with 13F managers based on the overlap between quarterly trades inferred from both datasets. I manually verify the potential matches based on manager names. Then, I merge ANcerno daily transactions with original/confidential 13F holdings reports. I identify any buy trades as informed (uninformed) if the stocks bought during a quarter can be matched with confidential (original) holdings for that quarter. This process allows for informed trades to be separated from uninformed ones. I only consider buys because short positions are typically not reported in the 13F filings.

In order to examine how institutional investors break up large orders and spread them across brokers

[1]Section 13(f) of the Securities Exchange Act of 1934 requires institutional investors to disclose their quarterly portfolio holdings to public. Form 13F filings reports holdings information as of each calendar quarter-end and Form 13F must be filed within forty-five days of the report date. However, investment managers may request the confidential treatment for certain holdings and omitting those holdings from Form 13F filings would be allowed until SEC makes a decision on the request.

and over time, I stitch together all child orders that are part of the same parent orders following Anand et al. (2012). Specifically, I stitch together all orders on the same stock on the same side of the market (buy or sell) by the same manager on behalf of the same client (simply referred to as client-manager or investment manager hereafter) that are executed through multiple brokers and over multiple consecutive trading days to construct parent orders. A parent order is a collection of child orders (tickets) on the same stock in the same direction that a fund may place with multiple brokers and over multiple days.

First, I find that investment managers tend to split their informed orders so that any given broker may not know the full size of the orders. Specifically, I find that informed trades are more spread out across more brokers over more trading days. This finding is more pronounced when I restrict my analysis to large orders (blocks), defined as parent orders with share volume greater than or equal to 10,000 shares or dollar volume greater than or equal to $200,000. Informed trades are not only spread out across a larger number of brokers, but they are also spread out more evenly across brokers, as measured by the Herfindahl-Hirschman Index (HHI) of dollar volume executed by each broker.[2] A concern is that my results could be driven by order size: informed orders could be larger and larger orders may simply require more brokers and take longer time to fill. However, my results are robust to controlling for order size.[3]

In addition to splitting and spreading out, I find that investment managers also camouflage their informed orders by mixing an informed order with other uninformed orders that are sent to the same broker on the same day. Interestingly, the brokers receiving informed orders not only receive orders on a larger number of stocks, they also receive a more evenly distributed volume of orders across stocks – so that informed orders are not readily distinguishable from uninformed ones. These results indicate that investment managers attempt to create their own noisy orders so as to hide their trading motives.

These order submission strategies that appear to be designed to conceal informed trades at the individual order level further lead to a high degree of randomization of order flows on a portfolio of orders

[2]HHI is calculated by squaring the portion of the traded aggregate dollar volumes through each broker for the fund and then summing the resulting numbers.

[3]I use three measures of the size of a parent order: the logarithm of the dollar volume of the parent order, the share volume of the parent order scaled by the daily trading volume reported in Center for Research in Security Prices (CRSP), and the share volume of the parent order scaled by the number of shares outstanding reported in CRSP.

sent across brokers. To show this, I aggregate for each client-manager all buy orders executed on the same day to construct a portfolio of orders on a daily basis. Then, I measure the extent to which a set of brokers used by an investment manager tend to overlap with or deviate from the set of brokers that the investment manager has used in the past. I ask, for instance, if manager $m$ submits her largest volume of orders to broker $b$ today, would broker $b$ also receive the largest order flows from manager $m$ tomorrow? Specifically, I measure the similarity between the set of brokers used by an investment manager today and the set of brokers used by the same manager one day later, two days later, up to twenty days later. The broker similarity is measured by cosine similarity based on the dollar volume of orders executed by each broker. I find that investment managers tend to submit their orders to a slightly different set of brokers each day. Looking across days that are further apart, the cosine similarity of the brokers used by each manager drops initially, but settles to a steady level in just a few days. This suggests that while shuffling order flows sent across brokers to hide informed orders, investment managers typically maintain close trading relationships with their core sets of brokers, that can facilitate liquidity provision when managers submit large liquidity-motivated orders (Han, Kim, and Nanda (2019)).

Next, I investigate why investment managers shuffle their orders across brokers each day. One reason for shuffling could be to maintain premium status with a large number of brokers and obtain valuable services such as access to sell-side research (Goldstein et al. (2009)). If a manager does not have a sufficient volume of orders to split on any given day, the manager may take turns submitting orders to different brokers in order to maintain close relationships with a large number of brokers. I argue that an alternative important motive for shuffling is to conceal informed orders. To test this, I measure similarity between today's set of brokers used by an investment manager and the core set of brokers used by the manager (from day t-25 to day t-6), as measured by cosine similarity based on the aggregate dollar volume of orders executed by each broker. I find that there is a larger share of informed trading volume on days when investment managers deviate from their core sets of brokers, that is, when the broker similarity is lower and the degree of shuffling is higher. This result is generally consistent with the randomization strategy envisioned in Yang and Zhu (Forthcoming) that investment managers can shuffle their order flows in order to conceal their informed orders. Again, a concern may be that investment managers trade larger quantities of shares on days with more informed trading volume and are naturally forced to send orders outside their core sets of brokers. However, the results are robust to controlling for trading volume, mitigating this concern.

So far my analysis has been limited to ANcerno client-managers for which ANcerno managers could be matched with 13F managers and limited to manager-quarters with confidential 13F filings. As a robustness check, I extend this analysis to the full ANcerno sample. On every trading day I sort funds into quantiles based on cosine similarity of the dollar volume of orders executed by each broker between the set of brokers used today by a fund and the core set of brokers used by the same fund (from day t-25 to day t-6). Then I measure the value-weighted buy-and-hold return on the stocks bought on each day by each client-manager, weighted by dollar volume, for the next month (typically from day t+1 to day t+21). For each quintile, I first average value-weighted returns across client-managers and then use the time series average value-weighted returns for statistical inference in the spirit of Fama and MacBeth (1973), adjusting for serial correlation up to a lag of 20 trading days following Newey and West (1987). I find that the most dissimilar quintile outperforms the most similar quintile by 24 basis points per month (t = 3.20). When adjusting for DGTW-benchmark returns (Daniel et al. (1997)), the return spread remains large and statistically significant at 17 basis points per month (t = 2.77). This full sample result corroborates the previous finding that investment managers shuffle their orders across brokers more on days with a larger share of informed trading volume.

An important question that remains is whether the splitting and shuffling strategies work for investment managers in terms of reducing trading costs on informed orders. Following the literature (e.g., Anand et al. (2012), Anand et al. (2013)), I measure institutional trading costs using the implementation shortfall. First, I examine individual parent orders. I find that splitting orders across brokers on any given day tends to reduce trading costs for informed orders, whereas splitting uninformed orders has little effect on implementation shortfall. Since the first day portion of multi-day orders could be larger than the later day portions, which could affect both splitting decisions and trading costs, I control for order-sequence fixed-effects (first day, second day, etc.). The result is robust to controlling for various fixed-effects and order size. Next, I restrict my analysis to multi-day orders (about 30% of parent orders) in order to examine how orders are sequenced and shuffled across brokers over time. Investment managers may avoid sending remaining parts of the large informed orders to the brokers that executed early parts of the orders in order to conceal the underling informed trading motives. Consistent with this prediction, sending later parts of the orders to new brokers (i.e., shuffling) tends to lower trading costs on informed orders. Again, this result is robust to controlling for various fixed-effects and order size.

Finally, I examine portfolios of orders at a daily level to test whether the shuffling strategy at the macro level works for investment managers. I find that dis-similarity between today's set of brokers used by a fund and the core set of brokers used by the same fund (one minus cosine similarity) is associated with lower trading costs as measured by implementation shortfall on informed orders. The result, combined with the earlier results, is consistent with investment managers shuffling informed orders across brokers and mixing informed orders with other uninformed orders sent to the same brokers, in order to mitigate trading costs on informed orders.

The remainder of the paper is organized as follows. Section 2 describes the data sources and the construction of my sample and variables. I report my results in Section 3. Section 4 concludes.

## 2 Data and Variable construction

My analysis of order submission strategies across brokers by informed traders exploits a detailed trade-level dataset that also contains information on institutional investors and their brokers. Another important requirement of my analysis is identifying whether a trade is information-motivated or not. I describe the institutional daily transaction data and how I construct my sample, and then explain how I identify informed trades.

I obtain institutional daily transactions from ANcerno data (also known as Abel Noser data).[4] My

[4]Other recent studies using ANcerno data to examine the behavior of institutional investors include Chemmanur, He, and Hu (2009); Chemmanur, Hu, and Huang (2010), Goldstein et al. (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand et al. (2012, 2013), Hu et al. (2014), Jame (2018), Barbon et al. (Forthcoming),

data cover equity transactions made by a large sample of institutions from January 1999 through December 2009. For each transaction, the data include the date of transaction, the stock traded (identified by both ticker and CUSIP), the number of shares traded, whether it is a buy or sell by the institution, the transaction price, various benchmark prices, the broker executing the trade, and commissions paid to the broker. Using an algorithm similar to the ones used in Hu et al. (2018) and Choi et al. (2016), I match ANcerno managers (identified by managercode) and 13F managers (identified by CIK) by comparing quarterly changes in holdings computed from ANcerno data and 13F filings. In addition, ANcerno provided the names of investment managers in 2011. This enables me to use the manager names to manually verify the manager matches from ANcerno daily transactions database and 13F quarterly holdings reports.

Institutional investors tend to break up large orders and spread them across brokers and over time. In ANcerno data, observation units are those broken-up child orders, called tickets. Following Anand et al. (2012), I stitch together all child orders that are part of the same parent orders. Specifically, I stitch together all tickets on the same stock on the same side of the market (buy or sell) by the same manager on behalf of the same client (referred to as client-manager or investment manager hereafter) that are executed through multiple brokers over multiple consecutive trading days to construct parent orders. A parent order is just a collection of child orders on the same stock in the same direction that an investment manager may place with multiple brokers over multiple trading days.

Next, I identify informed trades using "confidential" 13F filings, following Agarwal et al. (2013). I directly retrieve both original 13F filings and all amendment filings (Form 13F-HR and Form 13F-HR/A[5]) dated between March 1999 and December 2009 from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. For the sake of data consistency and integrity, I extract information about the original 13F holdings directly from the EDGAR, rather than using Thomson Reuters' 13F institutional holdings database (s34). Amendments to 13F filings provide two types of information: (1) a change in a position that was reported in the original 13F filing and (2) a newly added position that was not reported

Ben-Rephael and Israelsen (2018), and Di Maggio et al. (2019).

[5]Form 13F-HR/A includes an indication on its cover regarding whether it is an "amendment" (i.e., whether it adds new holdings) or a "restatement." I only include forms with the "amendment" box checked.

in the original 13F filing. I define a holding as a "confidential" holding if there is a positive change in the position on the original filing or if it is a newly added position on an amendment filing. I note that a vast majority of confidential holdings are newly added positions that are disclosed later on the amendment filings. Figure 1 provides a timeline of the original and amendment 13F filings. I define any buy transaction from the ANcerno-13F merged dataset during a quarter as an informed (uninformed) trade if it can be matched with a confidential (original) holding at the quarter-end. I only consider buys because short positions are typically not reported in the 13F filings.

[Insert Figure 1]

My initial manager matching process gives rise to 129 ANcerno-13F managers. Out of those 129 managers, 61 managers have at least one quarter with confidential holdings. About 6 % of parant orders are considered informed orders. Panel A of Table 1 describes the characteristics of the parent orders. Parent orders are, on average, split across 1.74 brokers and over 1.38 trading days. Panel B of Table 1 describes the characteristics of the daily portfolios of orders.

[Insert Table 1]

Next, I measure the extent to which investment managers shuffle their order flows across brokers by the broker *dis*-similarity. First, I aggregate the dollar volume of buy orders on the same day by the same client-manager executed by each broker. Then, I calculate the cosine similarity between today's set of brokers used by an investment manager and the *core* set of brokers used by the same manager (from day $t-25$ to day $t-6$) based on the dollar volume of buy orders executed by each broker. This proxy captures how similar today's set of brokers used by an investment manager is to the set of brokers used by the same manager in the past 20 days, skipping the 5 days immediately preceding the current day. The broker *dis*-similarity is just one minus cosine similarity.

For a robustness check, I construct two additional measures to capture patterns of order flow shuffling across brokers. First, like the first measure, I aggregate the dollar volume of orders across the same client-manager and across each broker on the same day. I then consider the overlapping percentage volume executed by the brokers today and the brokers in the past 20 days (from day $t-25$ to day $t-6$). Second, I consider only one broker who executed the largest dollar volume for each client-manager during the past 20 days ($t-25$ to day $t-6$). I then calculate the fraction of today's dollar volume executed by the top broker based on the dollar volume in the past 20 days. If an investment manager keeps submitting orders to the same brokers, then there will be little shuffling and the broker similarity (*dis*-similarity) will be high (low). On the other hand, if an investment manager keeps submitting orders to different brokers, then there will be a lot of shuffling and the broker similarity (*dis*-similarity) will be low (high).

In order to examine how the order splitting and shuffling strategies affect institutional trading costs, I construct the implementation shortfall measure (the percentage change between the execution price and the benchmark price) at the ticket level. Specifically, following Keim and Madhavan (1997) and Anand et al. (2012, 2013), I calculate implementation shortfall as follows:

$$\frac{P_1(t) - P_0(t)}{P_0(t)} \times D(t) \tag{1}$$

where $P_1(t)$ is the volume-weighted execution price, $P_0(t)$ is the benchmark price prevailing at the time when a broker receives the order, and $D(t)$ is the sign of the trade ($+1$ for a buy and $-1$ for a sell).

# 3 Order Submission Strategies

I begin my empirical analysis by examining order submission strategies at the parent-order level in Section 3.1 and turn to examining order submission strategies at the portfolio level in Section 3.2. I first show how institutional investors place orders differently when trading on private information and then examine how the order submission strategies across brokers can affect institutional trading costs.

## 3.1 Analysis of Parent Orders

Following Anand et al. (2012), I stitch together all orders on the same stock on the same side of the market by the same client-manager that are executed through multiple brokers and over multiple consecutive trading days to construct parent orders. A parent order is just a collection of child orders (tickets) on the same stock in the same direction that an investment manager may place with multiple brokers over multiple trading days. I contend that, when trading on private information, institutional investors may spread their orders across more brokers and over more trading days in order to conceal their informed trading motives. As discussed in Section 1, this splitting strategy is consistent with many theoretical models of informed trading, starting with Kyle (1985) and Easley and O'Hara (1987).

In order to test this hypothesis, I identify information-motivated orders by combining ANcerno daily transactions with 13F quarterly holdings (both original and confidential). Specifically, a parent buy order during a quarter that can be matched with a holding at the end of the quarter for which an investment manager has sought confidentiality treatment is identified as an informed trade. In other words, informed buy orders end up appearing on the manager's confidential 13F filings, but not on the original 13F filings, whereas uninformed buy orders end up appearing on the manager's original 13F filings on the report date at the end of the quarter. Intuitively, an attempt to hide their positions by seeking confidentiality treatment implies that managers have traded those stocks acting on their superior private information. Indeed, Agarwal et al. (2013) show that confidential holdings tend to outperform original holdings.

Having separated information-motivated orders from uninformed ones, I estimate the following linear regression model:

$$Number\ of\ Days_{i,k,s,t} = \beta \times \mathbb{1}(Informed\ Motivated_{i,k,s,t}) + \alpha_{i,k} + \rho_s + \theta_t + \varepsilon_{i,k,s,t} \tag{2}$$

where $i$ indexes managers, $k$ indexes clients, $s$ indexes stocks, and $t$ indexes dates on which parent orders were initially placed. The dependent variable is the number of days for which parent orders are extended ($Number\ of\ Days_{i,k,s,t}$) or the number of brokers to which parent orders are sent ($Number\ of\ Brokers_{i,k,s,t}$) or the broker's Herfindahl-Hirschman Index ($Broker\ HHI_{i,k,s,t}$), which measures the degree of concentration (or diversification) across brokers to which a parent order is sent, calculated by squaring a fraction of the dollar volume executed by each broker and summing it over all brokers to which a parent order is submitted. The independent variable of interest, $\mathbb{1}(Informed\ Motivated_{i,k,s,t})$, is an indicator variable that takes the value of one if a parent order is motivated by information and zero otherwise. Depending on the specification, the regression includes client-manager fixed effects ($\alpha_{i,k}$) and stock fixed effects ($\rho_s$). All regressions include time fixed effects ($\theta_t$), and standard errors are clustered by client-managers.

The baseline regression results are presented in Panel A of Table 2. In columns (1) and (2), the dependent variable is $\textit{Number of Days}_{i,k,s,t}$. In column (1), the coefficient of $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ is positive and statistically significant at the 1% level. This is consistent with my hypothesis that institutional investors are more likely to split their order across multiple days when trading on private information. The result remains largely unchanged when controlling for stock fixed effects in column (2). In columns (3) and (4), the dependent variable is $\textit{Number of Brokers}_{i,k,s,t}$. In column (3), the coefficient of $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ is positive and statistically significant at the 1% level. This suggests that institutional investors tend to place orders across more brokers when the orders are motivated by private information. Also, the result remains robust when controlling for stock fixed effects. In columns (5) and (6), I replace $\textit{Number of Brokers}_{i,k,s,t}$ with $\textit{Broker HHI}_{i,k,s,t}$ in the above linear regression model. *Broker HHI* measures the degree of concentration across brokers to which a parent order is sent and is calculated by squaring a fraction of the dollar volume executed by each broker and summing it over all brokers to which a parent order is submitted. A lower *Broker HHI* implies that a parent order is spread out across a more diversified set of brokers. I contend that informed orders are more likely to be sent across a diversified set of brokers in order to hide the information content of the orders from the brokers and other market participants. In columns (5) and (6), $\mathbb{1}(\textit{Informed Motivated})$ is negatively associated with *Broker HHI* and statistically significant at 1%, with or without controlling for stock fixed effects. This implies that informed orders are sent in a scattered way across brokers when compared to uninformed orders.

One might be concerned that my results could be driven by order size. In other words, informed orders could be larger, and larger orders may require more days and more brokers to fill. In order to address this concern, I re-run the tests in a sub-sample of large orders ("blocks"), defined as parent orders with share volume greater than or equal to 10,000 shares or dollar volume greater than or equal to $200,000. The regression results are presented in Panel B of Table 2. I continue to find qualitatively similar, even stronger, results that large informed orders are spread over more days and sent across more brokers than large uninformed orders. In addition, I control for several proxies to control for effects related to order size: log of dollar volume, share volume as percentage of CRSP volume, and share volume as percentage of the number of shares outstanding. The results are reported in Panel C, Panel D, and Panel E, respectively. I continue to obtain qualitatively similar results.

[Insert Table 2]

From the previous analysis, I find that institutional investors tend to spread out their informed orders across more brokers and over more trading days. An important question that remains is whether such order submission strategies work for institutional investors in terms of reducing trading costs. I argue that if they are effective in concealing informed trading motives, those order submission strategies should reduce trading costs on informed orders. I compute the implementation shortfall, which is the percentage change between the execution price and a benchmark price as the transaction cost (Keim and Madhavan (1997) and Anand et al. (2012, 2013)).

In order to test whether splitting orders across brokers are effective in reducing trading costs, I estimate the following linear regression model:

$$\begin{aligned} \textit{Implementation Shortfall}_{i,k,s,b,d,t} = {} & \delta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) \times \mathbb{1}(\textit{Multiple Brokers}_{i,k,s,t}) \\ & + \beta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) + \lambda \times \mathbb{1}(\textit{Multiple Brokers}_{i,k,s,t}) \\ & + \alpha_{i,k} + \gamma_d + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,d,t} \end{aligned} \tag{3}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, and $t$ indexes trading days. The dependent variable, $\textit{Implementation Shortfall}_{i,k,s,b,t}$, is the percentage difference between the execution price and the benchmark price. As before, $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ is an indicator variable that takes the value of one if the order is driven by information. $\mathbb{1}(\textit{Multiple Brokers}_{i,k,s,t})$ is an indicator variable that takes the value of one if the order is split up across multiple brokers on that trading day and zero otherwise. Depending on the specification, the regression includes client-manager fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), broker fixed effects ($\eta_b$), and time fixed effects ($\theta_t$). All regressions include order-sequence fixed effects ($\gamma_d$) to control for unobserved characteristics of child orders that are executed on the first day, second day, and so on, as part of parent orders. As before, standard errors are clustered by client-manager.

The regression results are presented in Panel A of Table 3. Consistent with my prediction, splitting across multiple brokers to execute an order can lower trading costs, especially on informed orders. I continue to find qualitatively similar results after controlling for order size using log of dollar volume in Panel B. Furthermore, when I restrict my analysis to sub-samples that only includes multi-day parent orders in Panels C and D, I find the coefficient of the interaction term between $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) \times \mathbb{1}(\textit{Multiple Brokers}_{i,k,s,t})$ to be much greater than the one from the full sample. This result suggests that the effect of spreading out informed orders across multiple brokers on trading costs is more pronounced when the orders extend multiple days.

[Insert Table 3]

In the previous analysis, I considered the *static* strategy of splitting orders across multiple brokers on the *same* trading days, thus muting the time dimension. Next, I consider the *dynamic* strategy of splitting orders across brokers *across* multiple trading days. I contend that later parts of informed orders would be sent to different brokers from the ones that initially executed early parts of the same parent orders. Such dynamic order splitting strategies can help prevent any single broker from learning the full size and information content of the orders, thereby mitigating trading costs. To test this prediction, I estimate the following linear regression model:

$$\begin{aligned}\textit{Implementation Shortfall}_{i,k,s,b,d,t} &= \delta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) \times \mathbb{1}(\textit{Different Broker}_{i,k,s,t}) \\ &+ \beta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) + \lambda \times \mathbb{1}(\textit{Different Broker}_{i,k,s,t}) \\ &+ \alpha_{i,k} + \gamma_d + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,d,t}\end{aligned} \tag{4}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, $d$ indexes order-sequence, and $t$ indexes trading days. The dependent variable, $\textit{Implementation Shortfall}_{i,k,s,b,t}$, is the percentage difference between the execution price and the benchmark price. As before, $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ is an indicator variable that takes the value of one if the order is driven by information. $\mathbb{1}(\textit{Different Broker}_{i,k,s,t})$ is an indicator variable that takes the value of one if an order is sent to a different broker from the ones that executed early parts of its parent order on the first trading day. Depending on the specification, the regression includes client-manager fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), broker fixed effects ($\eta_b$), and time fixed effects ($\theta_t$). All regressions include order-sequence fixed effects ($\gamma_d$) and standard errors are clustered by client-manager.

The regression results are presented in Table 4. The above analysis is naturally restricted to a subsample of child orders that are part of multi-day parent orders and that are executed on the second day or later days. As before, I control for order-sequence fixed effects, essentially comparing second-day informed orders to second-day uninformed orders, third-day informed orders to third-day uninformed orders, and so forth. Consistent with my prediction, I find that submitting later parts of informed orders to different brokers from the ones that initially executed early parts of the same parent orders are effective in reducing trading costs. Again, I continue to find qualitatively similar results after controlling for order size, as shown in Panel B.

[Insert Table 4]

## 3.2 Analysis of Order Portfolios

In the previous subsection, I examined institutional order submission strategies at the parent-order level. In this subsection, I extend my analysis to order portfolios and examine macro-level strategies. First, I examine the order "camouflaging" strategy that can serve as a bridge between the analysis of parent orders and that of order portfolios. Then, I examine the order ”shuffling” strategy at the order-portfolio level, which combines the dynamic order splitting strategy that was considered in the previous subsection and the order camouflaging strategy in this subsection.

My analysis of order submission strategies at the parent-order level provides evidence that institutional investors tend to spread their orders across more brokers and over more days when trading on information. Moreover, the order splitting strategies (both static and dynamic) tend to reduce trading costs by enabling informed traders to conceal their trading motives. Here I examine a different type of order submission strategy that can achieve the same goal: order camouflaging strategy. When submitting an informed order to a broker, the informed trader may submit uninformed orders simultaneously to the same broker, essentially creating its own noisy orders.

In order to test this prediction, I estimate the following linear regression model:

$$\textit{log(Number of Stocks)}_{i,k,b,t} = \beta \times \mathbb{1}(\textit{Informed Order to Broker}_{i,k,b,t}) + \alpha_{i,k} + \eta_b + \theta_t + \varepsilon_{i,k,b,t} \tag{5}$$

where $i$ indexes managers, $k$ indexes clients, $b$ indexes brokers, and $t$ indexes time in trading days. The dependent variable, $\textit{log(Number of Stocks)}_{i,k,b,t}$, is the number of stocks that broker $b$ receives from client-manager $i$-$k$ on trading day $t$. The independent variable of interest, $\mathbb{1}(\textit{Informed Order to Broker}_{i,k,b,t})$ is an indicator variable that takes the value of one if broker $b$ receives at least one informed order from client-manager $i$-$k$ on trading day $t$. Depending on the specification, the regression includes includes client-manager fixed effects ($\alpha_{i,k}$), broker fixed effects ($\eta_b$), and time fixed effects ($\theta_t$). Standard errors are clustered by client-manager.

The results are reported in Table 5. In columns (1)-(3) of Panel A, I find that investment manager tend to submit a greater number of stocks to a broker to whom they submit informed orders. Moreover, I find similar results after controlling for order size using log of dollar volume in columns (4)-(6). As a robustness check, I replace $\textit{log(Number of Stocks)}_{i,k,b,t}$ with $\textit{Stock HHI}_{i,k,b,t}$. $\textit{Stock HHI}_{i,k,b,t}$ is calculated by squaring the fraction of the dollar volume traded on each stock and then summing up across all stocks that a broker receives. The results suggest that when submitting an informed order to a broker, the informed trader tends to submit a more evenly distributed portfolio of orders in terms of dollar volume. These strategies are consistent with the institutional investors attempting to hide informed orders by creating their own noisy orders.

[Insert Table 5]

Order submission strategies designed to hide informed trades at the individual order level also lead to a large degree of randomization of order flows across brokers at the order portfolio level. To see how institutional investors keep submitting their orders to different brokers over time, I measure the extent to which a set of brokers an investment manager uses overlap with or deviate from the set of brokers the same manager has used in the past. Specifically, I measure the cosine similarity between today's set of brokers used by an investment manager and the set of brokers used by the same manager one day later, two days later, all the way through twenty days later, based on the dollar volume of orders executed by each broker. Figure 2 shows that investment managers tend to submit their orders to a slightly different set of brokers every day. Looking across days that are further apart, the broker similarity further drops, but at a decreasing rate, and starts to converge in a few days. This suggests that while shuffling order flows across brokers to hide informed orders, investment managers typically maintain close trading relationships with their core sets of brokers, since brokerage connections can help mitigate trading costs on large liquidity-motivated orders (Han, Kim, and Nanda (2019)).

[Insert Figure 2]

An important question at this point is why institutional investors shuffle their order flows across brokers everyday. One reason could be to maintain premium status with a large number of brokers and receive valuable services such as access to sell-side research (Goldstein et al. (2009)) Another important motive for shuffling could be to hide informed orders from the brokers. To answer this question, I examine whether a degree of order shuffling is associated with an extent of informed trading volume. To this end, I measure the broker *dis*-similarity between today's set of brokers used by a client-manager and the core set of brokers used by the same manager (from $t-25$ to day $t-6$), as measured by one minus cosine similarity based on the dollar volume of orders executed by each broker. Then, I estimate the following linear regression model:

$$Dis\text{-}similarity_{i,k,t} = \beta \times \mathbb{1}(Informed\ Shares_{i,k,t} > 0.5) + \alpha_{i,k} + \theta_t + \varepsilon_{i,k,t} \tag{6}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes time. The dependent variable, $Dissimilarity_{i,k,t}$, is one minus cosine similarity of broker usage of today and that from day $t-25$ to day $t-5$. The independent variable of interest, $\mathbb{1}(\mathit{Informed\ Shares}_{i,k,t} > 0.5)$ is an indicator variable that takes the value of one if more than half of dollar trading volume is driven by information. Depending on the specification, the regression includes client-manager fixed effects ($\alpha_{i,k}$) and time fixed effects ($\theta_t$) and standard errors are clustered by client-manager.

The regression results are presented in Panel A of Table 6. In column (1), the coefficient of $\mathbb{1}(\mathit{Informed\ Shares}_{i,k,t} > 0.5)$ is positive and statistically significant at the 1% level, which is consistent with my prediction that there is a higher degree of order shuffling across brokers on days with a larger share of informed trading volume. This result remains robust when controlling for time fixed effects in column (2). A possible concern about my results is that large orders can make investors order through various brokers, which can lead to higher dissimilarity. I control for log of dollar volumes, the number of shares traded, and the number of stocks traded on the same day to mitigate the concerns about order size. I find qualitatively similar results after controlling for these proxies for the order size in columns (4)-(6).

Similarly, I provide additional robustness checks by constructing more measures of dissimilarity. The first measure is one minus the overlapped dollar volumes traded through the set of brokers used by an investment manager and the set of brokers used by the same manager in the past. For the third measure, I compute how much the manager-client trades through their top broker, which is chosen based on the trading information from 25 to 5 days before the current day (i.e., today). I replace cosine similarity with the computed measure. These results are reported in Panel B and Panel C of Table 6, respectively. My results are robust when I use different measures of dissimilarity.

[Insert Table 6]

By research design, my analysis is limited to ANcerno manager-client pairs (funds) where ANcerno managers can be matched with 13F managers and manager-quarters when confidential filings. I extend the previous analysis to the full ANcerno sample. I examine the effect of the randomization strategy across brokers on performance. Every trading day I sort funds into quantiles based on similarity based on cosine similarity based on the dollar volume of orders executed by each broker between today's set of brokers used by a fund and the core set of brokers used by the same fund (from day t-25 to day t-6). Then I measure the value-weighted buy-and-hold return on the stocks bought on each day by each fund, weighted by dollar volume, for the next month (typically from day t+1 to day t+21). For each quintile, I first average value-weighted returns across funds then use the time series average value-weighted returns for statistical inference in the spirit of Fama and MacBeth (1973) and adjust for serial correlation up to a lag of 20 trading days following Newey and West (1987). I find that the most dissimilar quintile outperform the most similar quintile by 24 basis points per month (t = 3.20). When adjusting for DGTW-benchmark returns (Daniel et al. (1997)), the return spread remains large and statistically significant at 17 basis points per month (t = 2.77). This full sample result corroborates the previous finding that investment managers shuffle their orders across brokers more on days with a larger share of informed trading volume.

[Insert Table 7]

When institutional investors are trading on their private information, they believe that the information will eventually be publicly disclosed and the price will reflect the information, accordingly. However, they want to maximize their possible profits from this information. The primary prediction that I can derive from my hypothesis is that a randomization strategy across brokers can deter brokers from leaking private information, thereby reducing trading costs on informed orders. I compute implementation shortfall which is the percentage difference between the execution price and a benchmark price as transaction costs. (Keim and Madhavan (1997) and Anand et al. (2012, 2013)) This measure is at manager-client-stock-broker-day. Then, I interact dissimilarity measure with the indicator variable for identifying information motivated trade and estimate the following linear regression model:

$$\begin{aligned} \textit{Implementation Shortfall}_{i,k,s,b,t} = \delta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) \times \textit{Dissimilarity}_{i,k,t} \\ + \beta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) + \lambda \times \textit{Dissimilarity}_{i,k,t} \\ + \alpha_i + \gamma_k + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,t} \end{aligned} \tag{7}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, and $t$ indexes time in day. The dependent variable $\textit{Implementation Shortfall}_{i,k,s,b,t}$, is the percentage difference between the execution price and a benchmark price. The independent variable of interest, $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ denotes whether the order is driven by informed reason or not and $\mathit{Dissimilarity}_{i,k,t}$ is $1-$cosine similarity between the set of manager-client's aggregate trading dollar volume through its broker at today and that from 25 days before to 5 days before today. Depending on the specification, the regression includes manager $\times$ client (fund) fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), and broker fixed effects ($\eta_b$). All regressions include time fixed-effects ($\theta_t$) and standard errors are clustered by manager $\times$ client.

Panel A of Table 8 reports the results. Consistent with my prediction, I find a negative and statistically significant coefficient on $\mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t}) \times \mathit{Dissimilarity}_{i,k,t}$ and I continue to find the robust results after using different specifications including several fixed effects in columns (1)-(3). The estimates are also economically significant as the implementation shortfall decrease at around 12 bps. In contrast, the coefficients on $\mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t})$ are positive and statistically significant. The results suggest that more randomizing order flows across brokers can reduce the execution cost by hiding the true intention of order. Moreover, even though the coefficient on $\mathit{Dissimilarity}_{i,k,t}$ is not statistically insignificant, it is positive. Potentially, it can be interpreted as that more shuffling order flows across brokers can be relatively more expensive, thereby increase transaction costs. Moreover, I re-run the regression by using sub-sample which includes block orders (the aggregate volume of trade is greater than equal to 10,000 shares or the aggregate dollar volumes of trade is greater than equal to $200,000). Then I continue to obtain qualitative similar but much stronger magnitude of coefficients in columns (4)-(6).

Since trading volume can not only impact on price but also can contain information itself, I control for order sizes by using several proxies capture effects of order size. They are log of dollar volumes, log of volumes, percentage of shares traded in CRSP volume, and percentage of shares traded in outstanding shares. The results are reported in Panel B and C respectively. I continue to obtain qualitatively similar results.

[Insert Table 8]

### 3.3 Robustness Checks

In this subsection, I demonstrate the robustness of my main results regarding splitting and shuffling strategy by extending sample to the full ANcerno sample. For the main results, I separate information-motivated orders from uninformed ones by matching ANcerno transaction data with confidential 13F filings. Unfortunately, this process results in a large loss of data, as it requires matching ANcerno managers and 13F managers, yet not all ANcerno-13F matched managers seek confidentiality treatment on their holdings. Therefore, I extend the analysis to the entire ANcerno dataset to corroborate my main findings by using a different proxy to identify informed orders. Form 13F requires that all investment managers who have investment discretion over $100 million or more in Section 13(f) securities to disclose their quarter-end holdings in these securities (Agarwal et al. (2013)). If private information arrives near the quarter end, an investment manager might want to delay building a large position until the new quarter starts in order to avoid prematurely reporting a new informed position. In addition, investment managers may exert more effects into acquiring private information early in the quarter for the same reason. Hence, investment managers are likely to trade more heavily on private information earlier in the quarter. Based on this understanding, I estimate the following linear regression model:

$$\textit{Number of Days}_{i,k,s,t} = \beta \times \textit{Days to Quarter-end}_{i,k,s,t} + \alpha_{i,k} + \rho_s + \theta_t + \varepsilon_{i,k,s,t} \tag{8}$$

where $i$ indexes managers, $k$ indexes clients, $s$ indexes stocks, and $t$ indexes first trading days on which parent orders were placed. The dependent variable is the number of days for which parent orders extend ($\textit{Number of Days}_{i,k,s,t}$) or the number of brokers to which parent orders are sent ($\textit{Number of Brokers}_{i,k,s,t}$) or broker Herfindahl-Hirschman Index ($\textit{Broker HHI}_{i,k,s,t}$) which measures the degree of concentration across brokers to which a parent order is sent, calculated by squaring a fraction of the dollar volume executed by each broker and summing it over all brokers to which a parent order is submitted. The independent variable of interest, Days to Quarter-end$_{i,k,s,t}$, is the number of days from the first day on which a parent order is submitted to the calendar quarter-end. Depending on the specification, the regression includes manager×client (fund) fixed-effects ($\alpha_{i,k}$), stock fixed-effects ($\rho_s$) and quarter fixed-effects ($\theta_t$). Standard errors are clustered by manager × client (fund) for all regressions.

The results are reported in Panel A of Table A1. In columns (1) and (2), the coefficient of Days to Quarter-end$_{i,k,s,t}$ is positive and statistically significant at the 1% level, controlling for various fixed effects. This suggests that trade orders executed early in the quarter (presumably informed orders) require more days to complete. In columns (3) and (4), the coefficient of Days to Quarter-end$_{i,k,s,t}$ is positive and statistically significant, implying that orders tend to be placed across more brokers earlier in the quarter. From columns (5) and (6), I replace *Broker HHI*$_{i,k,s,t}$ with *Broker HHI*$_{i,k,s,t}$. I find that trades in the earlier period of the quarter are more likely to be sent across a diversified set of brokers. In order to mitigate concerns that my results could be driven by order size, I re-run the same linear regression in a sub-sample of large orders. However, the results reported in Panel B of Table A1 remain qualitatively similar and somewhat stronger. Overall, the results suggest that informed orders identified as those executed early in the quarter are likely spread over more days across more brokers and consistent with my prediction that investment managers attempt to conceal information content of orders from the brokers. As a robustness check, I control for several measures of order size: log of dollar volumes, percentage of shares traded in CRSP volume, and percentage of shares traded in outstanding shares. The results are reported in Panel C, Panel D, and Panel E, respectively. I continue to obtain qualitatively similar results.

[Insert Table A1]

Examining trades executed during the earlier period of quarter is allowing me not to lose lots of observations. Hence, I regress *Dissimilarity*$_{i,k,t}$ on *Days to Quarter-end*$_{i,k,t}$ including various fixed effects in the following linear regression model:

$$\textit{Dissimilarity}_{i,k,t} = \beta \times \textit{Days to Quarter-end}_{i,k,t} + \alpha_{i,k} + \theta_t + \varepsilon_{i,k,t} \tag{9}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes time. The dependent variable *Dissimilarity*$_{i,k,t}$, is 1−cosine similarity between the set of manager-client's aggregate trading dollar volume through its broker at today and that from 25 days before to 5 days before today. The independent variable of interest, *Days to Quarter-end*$_{i,k,t}$ is the number of days from the first day of order to quarter-end. Depending on the specification, the regression includes manager $\times$ client (fund) fixed effects ($\alpha_{i,k}$), and time fixed-effects ($\theta_t$) and standard errors are clustered by manager $\times$ client. The regression results are presented in Table A2. For all three proxies, I find that trades executed early in the quarter (presumably informed orders) tend to randomize their order flows across brokers. This evidence supports my hypothesis that investors are more likely to shuffle order flows across brokers when they are trading on their private information. This result is robust after controlling for various fixed effects and controlling daily aggregate dollar volumes, the number of shares traded, and the number of stocks traded.

[Insert Table A2]

# 4 Conclusion

In this paper, I study order submission strategies by institutional investors when trading on private information by exploiting proprietary data on institutional daily transactions. I separate informed orders from uninformed order by using 13F confidential holdings following Agarwal et al. (2013). I find that institutional investors tend to split orders over more days to complete the order and across more brokers when they are trading on private information. Furthermore, while institutional investors place uninformed large orders to the same brokers over multiple days, they tend to submit informed orders after the first day to new brokers who are different from the broker to whom they submitted orders on the first day.

Institutional investors not only shuffle their orders across brokers over time, but they also provide camouflage for their informed orders by mixing an informed order with other uninformed orders simultaneously sent to the same broker. As a result, a higher degree of shuffling a portfolio of orders is associated with a larger share of informed trading volume. The splitting and shuffling strategies designed to conceal informed trades from brokers and other market participants tend to lower institutional trading costs as measured by implementation shortfall, especially on informed orders.

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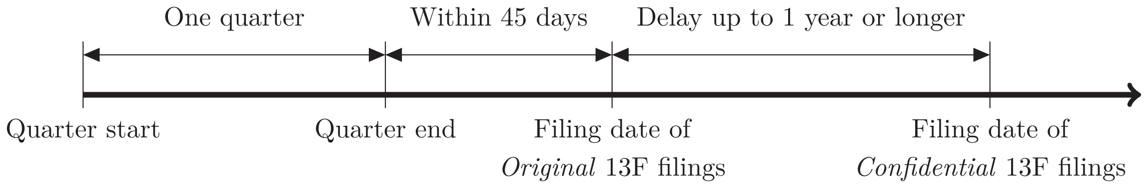


**Figure 1:** Timeline of the original and confidential 13F filings

This figure depicts timeline of the original and confidential 13F filings.

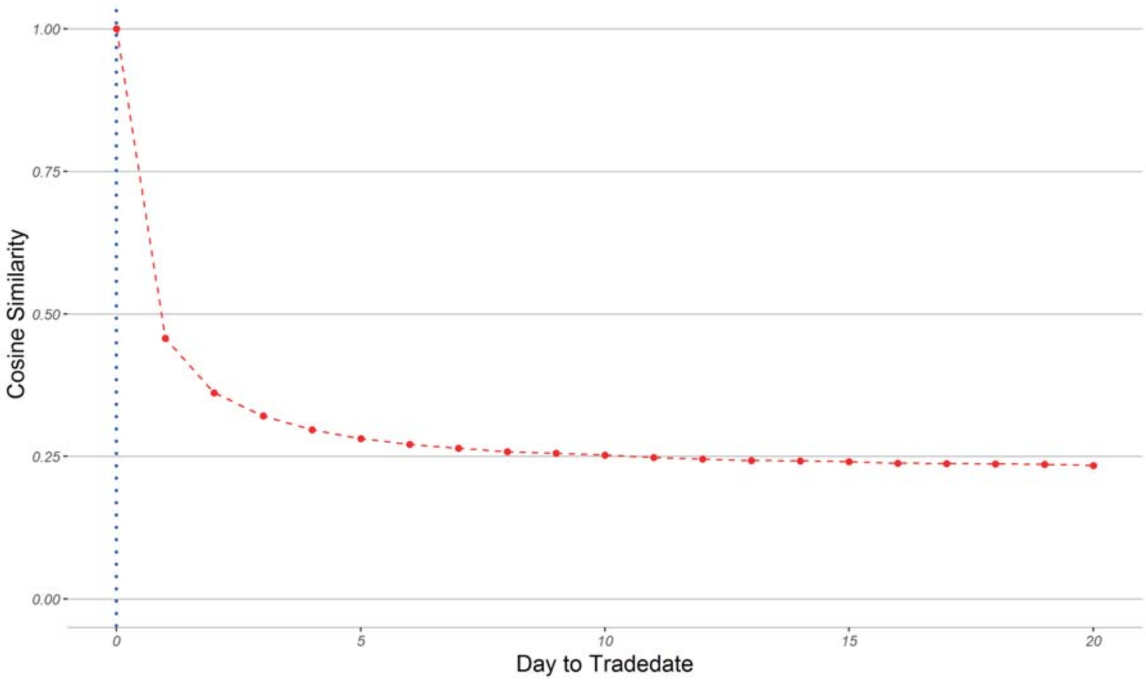


**Figure 2:** Shuffling order flows across brokers

This figure shows how different order flows across brokers day-to-day. I aggregate all buy side trades, by the same manager and client (fund), executed through the same broker, on the same day. Then I compute cosine similarity between today's set of brokers used by a manager-client (fund) and the set of brokers used by the same fund one day later, two days later, all the way through twenty days later based on the dollar volumes of orders executed by each broker.

## **Table 1:** Summary Statistics

This table reports the summary statistics. Panel A describes the characteristics of parent-order level (based on confidential holdings). I stitch all trades on the same stock, on the same side of market (focus on buy side), by the same manager and same client, continued day for the parent-order level. *nBrokers* is the number of brokers who worked for each parent order. *nDays* is how many days a parent order completed. *Broker HHI* measures the degree of concentration across brokers to which a parent order is sent, calculated by squaring a fraction of the dollar volume executed by each broker and summing it over all brokers to which a parent order is submitted. *Dollar Volume* is the total executed dollar volumes for a parent order and *volume (# of shares)* is the total number of shares executed through a parent order. *% in Trading Volume (CRSP)* (*% in Outstanding Volume (CRSP)*) is the executed volumes on the first day of each parent order scaled by CRSP trading volume (CRSP outstanding share) of the first day. $\mathbb{1}$(Informed Motivated) is an indicator variable if the executed stock of a parent order is contained in a confidential file or not. Panel B presents variables on daily order level. (Only buy side) Cosine similarity is calculated between the set of manager-client (fund)'s aggregate dollar volumes through its broker at today and that from 25 days before to 5 days before today (from $t-25$ to $t-6$). In a similar way, similarity (Top 1) is computed as how much manager-client (fund) trades through their top broker which is chosen based on trading information from 25 days before to 5 days before today (from $t-25$ to $t-6$). *% in Trading Volume (CRSP)* (*% in Outstanding Volume (CRSP)*) is the executed volumes on a day scaled by CRSP trading volume (CRSP outstanding share) of the day. Implementation shortfall is the percentage difference between the execution price and benchmark price. $\mathbb{1}$(Informed Motivated) is an indicator variable if the executed stock is contained in a confidential file or not. All the reported samples are merged with the sample of confidential holdings and I follow Agarwal et al. (2013) to identify confidential holdings.

| Variable | N | Mean | St. Dev. | $Q_1$ | Median | $Q_3$ |
|---|---|---|---|---|---|---|
| Panel A: Parent-order (Confidential Filings) | | | | | | |
| nBrokers | 214,250 | 1.38 | 0.88 | 1.00 | 1.00 | 1.00 |
| nDays | 214,250 | 1.74 | 1.84 | 1.00 | 1.00 | 2.00 |
| Broker HHI (x 100) | 214,250 | 91.42 | 18.35 | 100.00 | 100.00 | 100.00 |
| Dollar Volume ($ 000) | 214,250 | 1,756.51 | 6,910.29 | 32.98 | 154.75 | 802.07 |
| Volume (# of shares) | 214,250 | 72,035.19 | 330,360.10 | 1,100.00 | 5,600.00 | 31,800.00 |
| % in Trading Volume (CRSP) | 214,242 | 2.31 | 7.21 | 0.04 | 0.24 | 1.38 |
| % in Outstanding Share (CRSP) | 214,250 | 1.50 | 5.46 | 0.03 | 0.17 | 0.93 |
| $\mathbb{1}$(Informed Motivated) | 214,250 | 0.04 | 0.21 | 0.00 | 0.00 | 0.00 |
| Panel B: Daily-order (Confidential Filings) | | | | | | |
| Cosine Similarity | 279,758 | 0.74 | 0.27 | 0.68 | 0.87 | 0.91 |
| Similarity(Top 1 Broker) | 279,758 | 0.12 | 0.15 | 0.05 | 0.10 | 0.10 |
| Dollar Volume ($ 000) | 279,758 | 1,053.63 | 2,337.25 | 29.27 | 172.48 | 862.83 |
| Volume (# of shares) | 279,758 | 43,225.40 | 91,528.08 | 1,200.00 | 9,000.00 | 40,000.00 |
| % in Trading Volume (CRSP) | 279,758 | 6.50 | 9.95 | 0.16 | 1.79 | 9.11 |
| % in Outstanding Share (CRSP) | 279,758 | 4.55 | 7.76 | 0.11 | 1.19 | 5.58 |
| Implementation Shortfall (%) | 279,758 | 0.10 | 1.49 | −0.43 | 0.01 | 0.61 |
| $\mathbb{1}$(Informed Motivated) | 279,758 | 0.08 | 0.28 | 0.00 | 0.00 | 0.00 |

**Table 2:** Split or Concentrate Large Orders? Evidence from Confidential Holdings

This table examines whether the informed trades tend to split orders across more days and more brokers. Specifically, I regress *Number of Days*$_{i,k,s,t}$ on $\mathbb{1}$(*Informed Motivated*$_{i,k,s,t}$) in my specification as follows:

$$\textit{Number of Days}_{i,k,s,t} = \beta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) + \alpha_{i,k} + \rho_s + \theta_t + \varepsilon_{i,k,s,t} \tag{10}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes the first day in parent order. The dependent variable, *Number of Days*$_{i,k,s,t}$, is the number of days in each parent order. In column (3) through (4), *Number of Days*$_{i,k,s,t}$ is replaced by *Number of Days*$_{i,k,s,t}$, which is the number of brokers in each parent order. In column (5) through (6), the dependent variable is replaced by *Broker HHI*$_{i,k,s,t}$ which is the measure of institutional investors' concentration on usage of brokers. The independent variable of interest, $\mathbb{1}$(*Informed Motivated*$_{i,k,s,t}$) denotes whether the order is driven by informed reason or not. Panel A presents the baseline results. In Panel B, I examine block trades which include a trade's volume is greater than or equal to 10,000 or its dollar volume is greater than or equal to 200,000. Panel C presents results when controlling for log(Dollar Volume). In Panel D, I control for trading volume, % in CRSP volume and I also control for trading volume, % in outstanding share in Panel E. Depending on the specification, the regression includes manager × client fixed effects ($\alpha_{i,k}$), and stock fixed effects ($\rho_s$). All regressions include time fixed-effects ($\theta_t$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Motivated) | 0.64*** | 0.48*** | 0.18*** | 0.18*** | −3.53*** | −3.14*** |
| | (3.49) | (4.05) | (3.79) | (3.60) | (−3.65) | (−4.13) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 |
| Adjusted $R^2$ | 0.12 | 0.17 | 0.13 | 0.16 | 0.12 | 0.15 |
| Panel B: Block Trade (Volume ≥ 10K or Dollar volume ≥ 200K) | | | | | | |
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Motivated) | 0.89*** | 0.61*** | 0.21*** | 0.22*** | −3.83*** | −3.28*** |
| | (8.79) | (9.56) | (10.85) | (7.77) | (−7.27) | (−6.68) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 104,522 | 104,522 | 104,522 | 104,522 | 104,522 | 104,522 |
| Adjusted $R^2$ | 0.14 | 0.23 | 0.14 | 0.18 | 0.12 | 0.15 |

**Table 2**–*Continued*

| Panel C: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 𝟙(Informed Motivated) | 0.57*** | 0.36*** | 0.14*** | 0.11*** | −2.82*** | −1.87*** |
| | (4.28) | (7.24) | (7.52) | (9.54) | (−6.25) | (−8.86) |
| log(Dollar Volume) | 0.28*** | 0.33*** | 0.17*** | 0.18*** | −3.00*** | −3.29*** |
| | (14.16) | (17.51) | (9.33) | (12.22) | (−11.65) | (−16.18) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 |
| Adjusted $R^2$ | 0.23 | 0.31 | 0.27 | 0.31 | 0.21 | 0.24 |

| Panel D: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 𝟙(Informed Motivated) | 0.60*** | 0.48*** | 0.18*** | 0.18*** | −3.46*** | −3.09*** |
| | (3.91) | (4.19) | (3.79) | (3.70) | (−3.88) | (−4.31) |
| Trading volume, % in CRSP volume | 2.97*** | 1.86*** | −0.19*** | 0.39 | −5.44** | −11.10** |
| | (5.41) | (3.52) | (−3.08) | (1.58) | (−2.11) | (−2.39) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 214,242 | 214,242 | 214,242 | 214,242 | 214,242 | 214,242 |
| Adjusted $R^2$ | 0.13 | 0.17 | 0.13 | 0.16 | 0.12 | 0.15 |

| Panel E: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 𝟙(Informed Motivated) | 0.60*** | 0.47*** | 0.18*** | 0.17*** | −3.34*** | −3.04*** |
| | (3.81) | (4.23) | (3.97) | (3.75) | (−4.02) | (−4.39) |
| Trading volume, % in Outstanding Share | 4.50*** | 2.83*** | 0.47*** | 0.90*** | −21.96*** | −21.28*** |
| | (6.23) | (4.61) | (3.21) | (3.04) | (−4.30) | (−3.65) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 | 214,250 |
| Adjusted $R^2$ | 0.13 | 0.17 | 0.13 | 0.16 | 0.12 | 0.15 |

**Table 3:** Less Implementation Shortfall with splitting order through Brokers

This table examines whether splitting order strategy can reduce trading costs or not. Specifically, I interact $\mathit{Split\ Brokers}_{i,k,s,t}$ with $\mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t})$ in my specification as follows:

$$\begin{aligned}\mathit{Implementation\ Shortfall}_{i,k,s,b,t} &= \delta \times \mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t}) \times \mathit{Split\ Brokers}_{i,k,s,t} \\ &+ \beta \times \mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t}) + \lambda \times \mathit{Split\ Brokers}_{i,k,s,t} \\ &+ \alpha_{i,k} + \gamma_d + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,d,t}\end{aligned}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, $d$ indexes order-sequence and $t$ indexes trade date. The dependent variable $\mathit{Implementation\ Shortfall}_{i,k,s,b,t}$, is the percentage difference between the execution price and a benchmark price. The independent variable of interest, $\mathbb{1}(\mathit{Informed\ Motivated}_{i,k,s,t})$ denotes whether the order is driven by informed reason or not and $\mathit{Split\ Brokers}_{i,k,s,t}$ is one if an institutional investor hires more than one broker, zero otherwise. (Daily Basis) In Panel B, I further control for trading dollar volumes. In Panel C and D, I use sub-sample which includes multi-day order. Depending on the specification, the regression includes manager × client (fund) fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), broker fixed effects ($\eta_b$), and time fixed-effects ($\theta_t$). All regressions include order-sequence fixed effects ($\gamma_d$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Baseline

| *Dependent variable:* | Implementation Shortfall (%) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(Split Brokers) × $\mathbb{1}$(Informed Motivation) | $-0.16^{***}$ | $-0.11^{***}$ | $-0.08^{***}$ | $-0.08^{**}$ |
| | (−3.61) | (−3.37) | (−2.65) | (−2.36) |
| $\mathbb{1}$(Informed Motivation) | $0.04^{**}$ | $0.05^{***}$ | $0.03^{***}$ | $0.03^{***}$ |
| | (2.56) | (3.66) | (2.80) | (2.77) |
| $\mathbb{1}$(Split Brokers) | −0.005 | −0.004 | 0.03 | 0.04 |
| | (−0.09) | (−0.06) | (0.61) | (0.79) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 425,219 | 425,219 | 425,219 | 425,219 |
| Adjusted $R^2$ | 0.02 | 0.11 | 0.13 | 0.13 |

**Table 3**–*Continued*

| Panel B: Robustness Checks | | | | |
|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(Split Brokers) × $\mathbb{1}$(Informed Motivation) | $-0.16^{***}$ | $-0.10^{***}$ | $-0.07^{**}$ | $-0.08^{**}$ |
| | (−3.52) | (−3.26) | (−2.36) | (−2.25) |
| $\mathbb{1}$(Informed Motivation) | $0.04^{***}$ | $0.05^{***}$ | $0.03^{**}$ | $0.03^{***}$ |
| | (2.83) | (4.00) | (2.43) | (2.78) |
| $\mathbb{1}$(Split Brokers) | −0.01 | −0.01 | 0.03 | 0.04 |
| | (−0.13) | (−0.10) | (0.64) | (0.80) |
| log(Dollar Volume) | $0.02^{*}$ | $0.02^{**}$ | $0.03^{***}$ | $0.03^{***}$ |
| | (1.90) | (1.97) | (3.46) | (2.70) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 425,219 | 425,219 | 425,219 | 425,219 |
| Adjusted $R^2$ | 0.02 | 0.11 | 0.13 | 0.13 |

| Panel C: Robustness Checks (Multi-Day order) | | | | |
|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(Split Brokers) × $\mathbb{1}$(Informed Motivation) | $-0.19^{***}$ | $-0.14^{**}$ | $-0.12^{*}$ | $-0.12^{*}$ |
| | (−2.71) | (−2.24) | (−1.92) | (−1.83) |
| $\mathbb{1}$(Informed Motivation) | $0.06^{***}$ | $0.09^{***}$ | $0.07^{***}$ | $0.06^{***}$ |
| | (4.08) | (6.63) | (5.26) | (4.67) |
| $\mathbb{1}$(Split Brokers) | −0.02 | −0.02 | 0.02 | 0.02 |
| | (−0.37) | (−0.32) | (0.30) | (0.38) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 262,895 | 262,895 | 262,895 | 262,895 |
| Adjusted $R^2$ | 0.02 | 0.12 | 0.14 | 0.15 |

**Table 3**–*Continued*

| Panel D: Robustness Checks (Multi-Day order) | | | | |
|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(Split Brokers) × $\mathbb{1}$(Informed Motivation) | −0.19*** | −0.14** | −0.12* | −0.12* |
| | (−2.70) | (−2.22) | (−1.86) | (−1.81) |
| $\mathbb{1}$(Informed Motivation) | 0.06*** | 0.09*** | 0.06*** | 0.06*** |
| | (3.99) | (6.36) | (4.80) | (4.48) |
| $\mathbb{1}$(Split Brokers) | −0.02 | −0.02 | 0.02 | 0.02 |
| | (−0.36) | (−0.31) | (0.40) | (0.42) |
| log(Dollar Volume) | 0.01 | 0.01 | 0.02*** | 0.02** |
| | (1.01) | (1.20) | (3.30) | (2.06) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 262,895 | 262,895 | 262,895 | 262,895 |
| Adjusted $R^2$ | 0.02 | 0.12 | 0.14 | 0.15 |

**Table 4:** Less Implementation Shortfall: Dynamics over Parent Order

This table examines dynamics of institutional investors' usage of brokers and shows sending orders to new brokers can help reduce trading costs. Specifically, I interact $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ with $\mathbb{1}(\textit{Order Sent to Different Broker}_{i,k,s,t})$ in my specification as follows:

$$\begin{aligned}\textit{Implementation Shortfall}_{i,k,s,b,t} &= \delta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) \times \mathbb{1}(\textit{Order Sent to Different Broker}_{i,k,s,t}) \\ &+ \beta \times \mathbb{1}(\textit{Informed Motivated}_{i,k,s,t}) + \lambda \times \mathbb{1}(\textit{Order Sent to Different Broker}_{i,k,s,t}) \\ &+ \alpha_{i,k} + \gamma_d + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,d,t}\end{aligned}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, $d$ indexes order-sequence, and $t$ indexes trade date. The dependent variable $\textit{Implementation Shortfall}_{i,k,s,b,t}$, is the percentage difference between the execution price and a benchmark price. The independent variable of interest, $\mathbb{1}(\textit{Informed Motivated}_{i,k,s,t})$ denotes whether the order is driven by informed reason or not and $\mathbb{1}(\textit{Order Sent to Different Broker}_{i,k,s,t})$ is one if an order is sent to different brokers after the first day, zero otherwise. In Panel B, I further control for trading dollar volumes. Depending on the specification, the regression includes manager × client (fund) fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), broker fixed effects ($\eta_b$), and time fixed-effects ($\theta_t$). All regressions include order-sequence fixed effects ($\gamma_d$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | |
|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | |
| | (1) | (2) | (3) | (4) |
| 𝟙(Order Sent to Different Broker) × 𝟙(Informed Motivation) | $-0.06^{***}$ | $-0.05^{**}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (−2.89) | (−2.46) | (−3.36) | (−3.31) |
| 𝟙(Informed Motivation) | 0.01 | $0.04^{*}$ | $0.04^{*}$ | $0.03^{*}$ |
| | (0.48) | (1.92) | (1.85) | (1.91) |
| 𝟙(Order Sent to Different Broker) | 0.0003 | −0.01 | 0.003 | 0.002 |
| | (0.04) | (−1.01) | (0.46) | (0.37) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 295,145 | 295,145 | 295,145 | 295,145 |
| Adjusted $R^2$ | 0.02 | 0.13 | 0.16 | 0.16 |

**Table 4**–*Continued*

| Panel B: Robustness Checks | | | | |
|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(Order Sent to Different Broker) × $\mathbb{1}$(Informed Motivation) | $-0.06^{***}$ | $-0.05^{**}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (−2.89) | (−2.47) | (−3.34) | (−3.32) |
| $\mathbb{1}$(Informed Motivation) | 0.01 | $0.05^{**}$ | $0.03^{*}$ | $0.03^{*}$ |
| | (0.54) | (2.07) | (1.70) | (1.82) |
| $\mathbb{1}$(Order Sent to Different Broker) | −0.001 | −0.01 | 0.002 | 0.003 |
| | (−0.13) | (−1.27) | (0.38) | (0.46) |
| log(Dollar Volume) | 0.01 | 0.01 | $0.02^{***}$ | $0.02^{**}$ |
| | (1.06) | (1.25) | (3.88) | (2.16) |
| Time Fixed-effects | No | Yes | Yes | Yes |
| Order Sequence Fixed-effects | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | No | Yes | Yes |
| Broker Fixed-effects | No | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes |
| Observations | 295,145 | 295,145 | 295,145 | 295,145 |
| Adjusted $R^2$ | 0.02 | 0.13 | 0.16 | 0.16 |

**Table 5:** Camouflage strategies: Evidence from Confidential Holdings

This table examines whether institutional investors submit more order to their brokers who would execute their informed order. (submitting camouflage orders to brokers) Specifically, I regress $\textit{log(Number of Stocks)}_{i,k,b,t}$ on $\mathbb{1}(\textit{Informed Order to Broker}_{i,k,b,t})$ in my specification as follows:

$$\textit{log(Number of Stocks)}_{i,k,b,t} = \beta \times \mathbb{1}(\textit{Informed Order to Broker}_{i,k,b,t}) + \alpha_{i,k} + \eta_b + \theta_t + \varepsilon_{i,k,b,t}$$

where $i$ indexes managers, $k$ indexes clients, $b$ indexes brokers, and $t$ indexes time. The dependent variable $\textit{log(Number of Stocks)}_{i,k,b,t}$, is the number of stocks which are executed through broker at manager-client-tradedate-broker level. The independent variable of interest, $\mathbb{1}(\textit{Informed Order to Broker}_{i,k,b,t})$ is an indicator variable which is equal to one if a investor submit at least one informed order to a broker, zero otherwise in Panel A. In Panel B, I replace $\textit{log(Number of Stocks)}_{i,k,b,t}$ with $\textit{Stock HHI}_{i,k,b,t}$. $\textit{Stock HHI}_{i,k,b,t}$ is calculated by squaring the portion of the traded aggregate volumes of each stock traded through a broker for investors and then summing the resulting numbers. I control for the number of shares. Depending on the specification, the regression includes includes manager $\times$ client (fund) fixed effects ($\alpha_{i,k}$), broker fixed effects ($\eta_b$), and time fixed-effects ($\theta_t$). Standard errors are clustered by manager $\times$ client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Baseline

| *Dependent variable:* | log(Number of Stocks) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Order to Broker) | 0.68*** | 0.72*** | 0.48*** | 0.55*** | 0.57*** | 0.39*** |
| | (3.76) | (3.68) | (9.80) | (6.03) | (5.90) | (19.78) |
| log(volume) | | | | 0.21*** | 0.21*** | 0.19*** |
| | | | | (3.88) | (3.85) | (6.37) |
| Time Fixed-effects | No | Yes | Yes | No | Yes | Yes |
| Broker Fixed-effects | No | No | Yes | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 142,383 | 142,383 | 142,383 | 142,383 | 142,383 | 142,383 |
| Adjusted $R^2$ | 0.41 | 0.42 | 0.55 | 0.55 | 0.56 | 0.65 |

Panel B: Robustness checks

| *Dependent variable:* | Stock HHI | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Order to Broker) | −18.78*** | −19.80*** | −13.82*** | −14.56*** | −15.16*** | −10.88*** |
| | (−4.29) | (−4.22) | (−12.20) | (−8.28) | (−8.15) | (−25.90) |
| log(volume) | | | | −6.67*** | −6.74*** | −6.12*** |
| | | | | (−4.85) | (−4.76) | (−8.49) |
| Time Fixed-effects | No | Yes | Yes | No | Yes | Yes |
| Broker Fixed-effects | No | No | Yes | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 142,383 | 142,383 | 142,383 | 142,383 | 142,383 | 142,383 |
| Adjusted $R^2$ | 0.36 | 0.37 | 0.46 | 0.47 | 0.48 | 0.54 |

**Table 6:** Randomizing Order Flows across Brokers: Evidence from Confidential Holdings

This table examines whether the information motivated order is more likely to shuffle the order flows across brokers. Specifically, I regress $Dissimilarity_{i,k,t}$ on $\mathbb{1}(Informed\ Shares > 0.5_{i,k,t})$ in my specification as follows:

$$Dissimilarity_{i,k,t} = \beta \times \mathbb{1}(Informed\ Shares > 0.5_{i,k,t}) + \alpha_{i,k} + \theta_t + \varepsilon_{i,k,t}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes time. The dependent variable $Dissimilarity_{i,k,t}$, is 1−cosine similarity between the set of manager-client's aggregate trading dollar volume through its broker at today and that from 25 days before to 5 days before today in Panel A. As a robustness check in Panel B of Table 6, I construct a dissimilarity measure by focusing top broker for manager-client. To be specific, I take only one broker who executed the largest dollar volume for the manager-client from 25 days before to 5 days before for every day. Then, the proxy is taking how much the manager-client place order through *the* top broker today in terms of the fraction of the aggregate dollar trading volumes. The independent variable of interest, $\mathbb{1}(Informed\ Shares > 0.5_{i,k,t})$ is a dummy variable identifying the day when enough informed trades happen. I control for several measures of order size which are daily aggregate dollar volumes, the number of shares, and the number of stocks. Depending on the specification, the regression includes manager × client (fund) fixed effects ($\alpha_{i,k}$) and time fixed-effects ($\theta_t$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on cosine similarity) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Shares > 0.5) | 4.48*** | 4.88*** | 3.16*** | 2.24** | 2.31** | 2.29** |
| | (3.83) | (3.83) | (2.79) | (2.04) | (2.12) | (2.10) |
| log(Dollar Volume) | | | −2.69*** | | 0.38 | |
| | | | (−4.69) | | (0.66) | |
| log(volume) | | | | | | 0.51 |
| | | | | | | (1.03) |
| log(NStocks) | | | | −7.11*** | −7.59*** | −7.73*** |
| | | | | (−6.39) | (−7.54) | (−7.00) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 |
| Adjusted $R^2$ | 0.43 | 0.49 | 0.50 | 0.52 | 0.52 | 0.52 |

| Panel B: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on overlapped dollar volumes) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Shares > 0.5) | 0.97** | 1.57*** | 1.53*** | 1.40** | 1.45** | 1.44** |
| | (2.09) | (2.62) | (2.65) | (2.53) | (2.57) | (2.57) |
| log(Dollar Volume) | | | −0.06 | | 0.24 | |
| | | | (−0.25) | | (1.09) | |
| log(volume) | | | | | | 0.33 |
| | | | | | | (1.49) |
| log(NStocks) | | | | −0.44 | −0.74* | −0.84* |
| | | | | (−1.08) | (−1.94) | (−1.91) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 |
| Adjusted $R^2$ | 0.59 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |

**Table 6**–*Continued*

| Panel C: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on Top Broker) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}$(Informed Shares > 0.5) | 2.63** | 2.86** | 2.76** | 2.52** | 2.60** | 2.58** |
| | (2.20) | (2.06) | (2.24) | (2.04) | (2.13) | (2.11) |
| log(Dollar Volume) | | | −0.15 | | 0.42 | |
| | | | (−0.21) | | (0.62) | |
| log(volume) | | | | | | 0.55 |
| | | | | | | (1.05) |
| log(NStocks) | | | | −0.90 | −1.42** | −1.57* |
| | | | | (−0.82) | (−1.98) | (−1.77) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 | 12,625 |
| Adjusted $R^2$ | 0.32 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 |

**Table 7:** Randomizing order submission strategies and institutional investors' performance

This table reports the monthly returns (raw-returns and Daniel et al. (1997) benchmark-adjusted returns) from January 1999 to November 2009. I sort funds into quantiles based on similarity based on cosine similarity based on the dollar volume of orders executed by each broker between today's set of brokers used by a fund and the core set of brokers used by the same fund (from day t-25 to day t-6). Then I measure the value-weighted buy-and-hold return on the stocks bought on each day by each fund, weighted by dollar volume, for the next month (typically from day t+1 to day t+21). For each quintile, I first average value-weighted returns across funds then use the time series average value-weighted returns for statistical inference in the spirit of Fama and MacBeth (1973) and adjust for serial correlation up to a lag of 20 trading days following Newey and West (1987). The heteroskedasticity robust t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| | cosine similarity | | | | | |
|---|---|---|---|---|---|---|
| | Similar($Q_1$) | $Q_2$ | $Q_3$ | $Q_4$ | Dis-similar($Q_5$) | D - S |
| Raw-Return | 0.76* | 0.85* | 0.93* | 0.98** | 1.01** | 0.24*** |
| | (1.69) | (1.80) | (1.93) | (2.06) | (2.14) | (3.20) |
| *DGTW-Adjusted Return* | 0.29*** | 0.34*** | 0.38*** | 0.45*** | 0.46*** | 0.17*** |
| | (3.81) | (4.78) | (5.15) | (6.07) | (6.22) | (2.77) |

**Table 8:** Less Implementation Shortfall with more shuffling Order Flows across Brokers

This table examines whether randomization strategy across brokers leads to decrease in trading costs or not. Specifically, I interact $Dissimilarity_{i,k,t}$ with $\mathbb{1}(Informed\ Motivated_{i,k,s,t})$ in my specification as follows:

$$\begin{aligned} Implementation\ Shortfall_{i,k,s,b,t} &= \delta \times \mathbb{1}(Informed\ Motivated_{i,k,s,t}) \times Dissimilarity_{i,k,t} \\ &+ \beta \times \mathbb{1}(Informed\ Motivated_{i,k,s,t}) + \lambda \times Dissimilarity_{i,k,t} \\ &+ \alpha_{i,k} + \rho_s + \eta_b + \theta_t + \varepsilon_{i,k,s,b,t} \end{aligned}$$

where $i$ indexes managers, $k$ indexes clients, $s$ index stocks, $b$ indexes brokers, and $t$ indexes time in day. The dependent variable $Implementation\ Shortfall_{i,k,s,b,t}$, is the percentage difference between the execution price and a benchmark price. The independent variable of interest, $\mathbb{1}(Informed\ Motivated_{i,k,s,t})$ denotes whether the order is driven by informed reason or not and $Dissimilarity_{i,k,t}$ is 1−cosine similarity between the set of manager-client (fund)'s aggregate trading dollar volume through its broker at today and the ones from 25 days before to 5 days before today. In columns (4)-(6), I examine block trades which include a trade's volume is greater than or equal to 10,000 or its dollar volume is greater than or equal to $200,000. Panel B presents results when controlling for log(Dollar Volume) or log (volume). In Panel C, I control for trading volume, % in CRSP volume or control for trading volume, % in outstanding share. Depending on the specification, the regression includes manager × client (fund) fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$), and broker fixed effects ($\eta_b$). All regressions include time fixed-effects ($\theta_t$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Implementation Shortfall (%) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dissimilarity × 𝟙(Informed Motivation) | −0.13*** | −0.12*** | −0.12*** | −0.41*** | −0.36*** | −0.37** |
| | (−2.86) | (−2.58) | (−2.58) | (−2.86) | (−2.64) | (−2.55) |
| Dissimilarity | 0.04 | 0.02 | 0.01 | 0.08 | 0.03 | 0.03 |
| | (0.93) | (0.39) | (0.28) | (0.88) | (0.33) | (0.31) |
| 𝟙(Informed Motivation) | 0.04*** | 0.02*** | 0.02** | 0.06*** | 0.03* | 0.03* |
| | (4.04) | (3.11) | (2.34) | (3.55) | (1.92) | (1.77) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | Yes | No | Yes | Yes |
| Broker Fixed-effects | No | No | Yes | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 279,758 | 279,758 | 279,758 | 148,864 | 148,864 | 148,864 |
| Adjusted $R^2$ | 0.09 | 0.11 | 0.11 | 0.09 | 0.11 | 0.11 |

**Table 8**–*Continued*

Panel B: Robustness

| *Dependent variable:* | Implementation Shortfall (%) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dissimilarity × 𝟙(Informed Motivation) | $-0.13^{***}$ | $-0.11^{**}$ | $-0.11^{**}$ | $-0.12^{***}$ | $-0.11^{**}$ | $-0.11^{**}$ |
| | (−2.78) | (−2.35) | (−2.48) | (−2.74) | (−2.36) | (−2.49) |
| Dissimilarity | 0.04 | 0.01 | 0.01 | 0.04 | 0.01 | 0.01 |
| | (0.89) | (0.27) | (0.26) | (0.88) | (0.28) | (0.27) |
| 𝟙(Informed Motivation) | $0.04^{***}$ | $0.02^{**}$ | $0.02^{**}$ | $0.04^{***}$ | $0.02^{**}$ | $0.02^{**}$ |
| | (3.97) | (2.22) | (2.02) | (3.73) | (2.20) | (2.00) |
| log(Dollar Volume) | $0.01^{**}$ | $0.02^{***}$ | $0.02^{**}$ | | | |
| | (1.99) | (6.00) | (2.47) | | | |
| log(volume) | | | | $0.01^{***}$ | $0.02^{***}$ | $0.01^{**}$ |
| | | | | (2.69) | (5.90) | (2.29) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | Yes | No | Yes | Yes |
| Broker Fixed-effects | No | No | Yes | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 279,758 | 279,758 | 279,758 | 279,758 | 279,758 | 279,758 |
| Adjusted $R^2$ | 0.09 | 0.11 | 0.11 | 0.09 | 0.11 | 0.11 |

Panel C: Robustness

| *Dependent variable:* | Implementation Shortfall (%) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dissimilarity × 𝟙(Informed Motivation) | $-0.13^{***}$ | $-0.14^{***}$ | $-0.14^{***}$ | $-0.13^{***}$ | $-0.12^{***}$ | $-0.12^{***}$ |
| | (−2.86) | (−3.01) | (−3.00) | (−2.73) | (−2.58) | (−2.63) |
| Dissimilarity | 0.04 | 0.02 | 0.01 | 0.04 | 0.02 | 0.01 |
| | (0.95) | (0.46) | (0.22) | (0.91) | (0.39) | (0.28) |
| 𝟙(Informed Motivation) | $0.04^{***}$ | $0.04^{***}$ | $0.03^{***}$ | $0.04^{***}$ | $0.02^{***}$ | $0.02^{**}$ |
| | (3.39) | (4.55) | (3.66) | (3.27) | (3.07) | (2.52) |
| % in Trading Volume | −0.07 | $-0.63^{***}$ | $-0.85^{***}$ | | | |
| | (−0.93) | (−4.78) | (−4.75) | | | |
| % in Outstanding Share | | | | $0.13^{*}$ | −0.02 | −0.18 |
| | | | | (1.67) | (−0.20) | (−1.33) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | Yes | No | Yes | Yes |
| Broker Fixed-effects | No | No | Yes | No | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 279,758 | 279,758 | 279,758 | 279,758 | 279,758 | 279,758 |
| Adjusted $R^2$ | 0.09 | 0.11 | 0.11 | 0.09 | 0.11 | 0.11 |

# Appendix

**Table A1:** Split or Concentrate Large Orders? Evidence from Order in earlier period of Quarters

This table examines whether the orders in earlier period of quarters tend to split the order across more days and more brokers. Specifically, I regress *Number of Days*$_{i,k,s,t}$ on *Days to Quarter-end*$_{i,k,s,t}$ in my specification as follows:

$$\textit{Number of Days}_{i,k,s,t} = \beta \times \textit{Days to Quarter-end}_{i,k,s,t} + \alpha_{i,k} + \rho_s + \theta_t + \varepsilon_{i,k,s,t}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes the first day in parent order. The dependent variable, *Number of Days*$_{i,k,s,t}$, is the number of days in each parent order. In column (3) through (4), *Number of Days*$_{i,k,s,t}$ is replaced by *Number of Days*$_{i,k,s,t}$, which is the number of brokers in each parent order. In column (5) through (6), the dependent variable is replaced by *Broker HHI*$_{i,k,s,t}$ which is the measure of institutional investors' concentration on usage of brokers. The independent variable of interest, Days to Quarter-end$_{i,k,s,t}$ is the number of days from the first day of order to quarter-end. Panel A presents the baseline results. In Panel B, I examine block trades which include a trade's volume is greater than or equal to 10,000 or its dollar volume is greater than or equal to 200,000. Panel C presents results when controlling for log(Dollar Volume). In Panel D, I control for trading volume, % in CRSP volume and I also control for trading volume, % in outstanding share in Panel E. Depending on the specification, the regression includes manager×client fixed effects ($\alpha_{i,k}$), stock fixed effects ($\rho_s$) and quarter fixed-effects ($\theta_t$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.001*** | 0.001*** | 0.001*** | 0.001*** | −0.01*** | −0.01*** |
| | (5.08) | (5.15) | (3.07) | (3.11) | (−2.95) | (−2.96) |
| Quarter Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 |
| Adjusted $R^2$ | 0.09 | 0.10 | 0.11 | 0.13 | 0.10 | 0.12 |

| Panel B: Block Trade (Volume ≥ 10K or Dollar volume ≥ 200K) | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.003*** | 0.003*** | 0.001*** | 0.001*** | −0.02*** | −0.02*** |
| | (4.27) | (4.23) | (2.85) | (3.08) | (−3.32) | (−3.65) |
| Quarter Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,344,741 | 3,344,741 | 3,344,741 | 3,344,741 | 3,344,741 | 3,344,741 |
| Adjusted $R^2$ | 0.16 | 0.18 | 0.22 | 0.24 | 0.17 | 0.18 |

**Table A1**–*Continued*

| Panel C: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.001*** | 0.001*** | 0.0004** | 0.0004** | −0.01** | −0.01** |
| | (4.32) | (4.32) | (2.31) | (2.30) | (−2.22) | (−2.20) |
| log(Dollar volume) | 0.20*** | 0.22*** | 0.16*** | 0.16*** | −2.92*** | −2.88*** |
| | (8.91) | (9.55) | (5.61) | (6.71) | (−6.61) | (−8.67) |
| Quarter Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 |
| Adjusted $R^2$ | 0.20 | 0.22 | 0.25 | 0.25 | 0.18 | 0.19 |

| Panel D: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.001*** | 0.001*** | 0.001*** | 0.001*** | −0.01*** | −0.01*** |
| | (5.03) | (5.11) | (3.09) | (3.13) | (−2.96) | (−2.97) |
| Trading volume, % in CRSP volume | 0.77 | 0.90*** | −1.27** | −0.18* | 29.12** | 9.05*** |
| | (1.43) | (3.57) | (−2.57) | (−1.74) | (2.12) | (2.75) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,099,641 | 10,099,641 | 10,099,641 | 10,099,641 | 10,099,641 | 10,099,641 |
| Adjusted $R^2$ | 0.09 | 0.10 | 0.11 | 0.13 | 0.10 | 0.12 |

| Panel E: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Number of Days | | Number of Brokers | | Broker HHI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.001*** | 0.001*** | 0.001*** | 0.001*** | −0.01*** | −0.01*** |
| | (5.01) | (5.09) | (3.09) | (3.10) | (−2.97) | (−2.96) |
| Trading volume, % in Outstanding Share | 16.21*** | 15.53*** | −8.50** | 6.11* | 229.12 | −29.07 |
| | (3.55) | (3.57) | (−2.06) | (1.68) | (1.56) | (−0.75) |
| Time Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed-effects | No | Yes | No | Yes | No | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 | 10,105,494 |
| Adjusted $R^2$ | 0.09 | 0.10 | 0.11 | 0.13 | 0.10 | 0.12 |

**Table A2:** Randomizing Order Flows across Brokers: Evidence from Order in earlier period of Quarters

This table provides further evidence whether the information motivated order is more likely to shuffle the order flows across brokers by looking at orders in earlier periods of quarter. Specifically, I regress $Dissimilarity_{i,k,t}$ on $Days\ to\ Quarter\text{-}end_{i,k,t}$ in my specification as follows:

$$Dissimilarity_{i,k,t} = \beta \times Days\ to\ Quarter\text{-}end_{i,k,t} + \alpha_{i,k} + \theta_t + \varepsilon_{i,k,t}$$

where $i$ indexes managers, $k$ indexes clients, and $t$ indexes time. The dependent variable $Dissimilarity_{i,k,t}$, is 1−cosine similarity between the set of manager-client's aggregate trading dollar volume through its broker at today and that from 25 days before to 5 days before today in Panel A. As a robustness check in Panel B of Table A2, I construct a dissimilarity measure by focusing top broker for manager-client. To be specific, I take only one broker who executed the largest dollar volume for the manager-client from 25 days before to 5 days before for every day. Then, the proxy is taking how much the manager-client place order through *the* top broker today in terms of the fraction of the aggregate dollar trading volumes. The independent variable of interest, $Days\ to\ Quarter\text{-}end_{i,k,t}$ is the number of days from the first day of order to quarter-end. I control for several measures of order size which are daily aggregate dollar volumes, the number of shares, and the number of stocks. Depending on the specification, the regression includes manager × client (fund) fixed effects ($\alpha_{i,k}$), and time fixed-effects ($\theta_t$). Standard errors are clustered by manager × client and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

| Panel A: Baseline | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on cosine similarity) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| | (7.71) | (8.44) | (11.23) | (9.39) | (9.88) | (9.79) |
| log(Dollar Volume) | | | −2.91*** | | −0.61*** | |
| | | | (−43.86) | | (−7.18) | |
| log(volume) | | | | | | −0.64*** |
| | | | | | | (−7.93) |
| log(NStocks) | | | | −6.62*** | −5.98*** | −5.95*** |
| | | | | (−47.59) | (−32.36) | (−33.67) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 |
| Adjusted $R^2$ | 0.25 | 0.25 | 0.26 | 0.28 | 0.28 | 0.28 |

| Panel B: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on overlapped dollar volumes) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (5.63) | (6.35) | (6.57) | (6.38) | (6.55) | (6.45) |
| log(Dollar Volume) | | | −0.14*** | | −0.13*** | |
| | | | (−4.33) | | (−2.78) | |
| log(volume) | | | | | | −0.07 |
| | | | | | | (−1.64) |
| log(NStocks) | | | | −0.17*** | −0.03 | −0.09 |
| | | | | (−3.23) | (−0.39) | (−1.25) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 |
| Adjusted $R^2$ | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 |

**Table A2**–*Continued*

| Panel C: Robustness checks | | | | | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | Dissimilarity × 100 (based on Top Broker) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Days to Quarter-end | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| | (7.41) | (7.99) | (8.39) | (8.07) | (8.31) | (8.20) |
| log(Dollar Volume) | | | −0.46*** | | −0.31*** | |
| | | | (−8.44) | | (−4.02) | |
| log(volume) | | | | | | −0.23*** |
| | | | | | | (−3.04) |
| log(NStocks) | | | | −0.72*** | −0.39*** | −0.48*** |
| | | | | (−8.05) | (−3.12) | (−3.96) |
| Time Fixed-effects | No | Yes | Yes | Yes | Yes | Yes |
| Manager × Client Fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 | 1,607,092 |
| Adjusted $R^2$ | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |