Performance of institutional trading desks: An analysis of persistence in trading costs

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Abstract

We contribute to the literature on the performance of financial intermediaries. Using a unique dataset of institutional investors' equity transactions, we document that institutional trading desks can sustain relative performance over adjacent periods. We investigate several possible explanations for trading cost persistence including broker selection, investment style, and commissions, and identify a set of trading decisions that are associated with performance. Our findings support the presence of skilled traders who can create positive (investment) alpha through their trading strategies. The substantial and persistent differences in institutional trading costs are large enough to significantly contribute to mutual fund performance persistence. We find that past broker performance can reliably predict future performance suggesting that broker selection based on past performance is an important dimension of money manager's fiduciary obligation.

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Abstract

We contribute to the literature on the performance of financial intermediaries. Using a unique dataset of institutional investors' equity transactions, we document that institutional trading desks can sustain relative performance over adjacent periods. We investigate several possible explanations for trading cost persistence including broker selection, investment style, and commissions, and identify a set of trading decisions that are associated with performance. Our findings support the presence of skilled traders who can create positive (investment) alpha through their trading strategies. The substantial and persistent differences in institutional trading costs are large enough to significantly contribute to mutual fund performance persistence. We find that past broker performance can reliably predict future performance suggesting that broker selection based on past performance is an important dimension of money manager's fiduciary obligation.

1. Introduction

Trading costs for institutional investors can be economically large.[1] One approach to measuring trading costs is to compare the returns of a real portfolio based on trades actually executed with those of a hypothetical, or paper, portfolio, whose returns are computed under the assumption that the security positions were acquired at midquote prices observed at the time of the trading decision. Perold (1988) named this performance difference, which captures the cumulative impact of trading costs such as commissions, bid ask spreads, and market impact, as "the implementation shortfall." From 1965 to 1986, Perold observes that, while the paper portfolio based upon the Value Line ranking system outperformed the market by 20% a year, the real ValueLine fund that makes the same trades recommended in the newsletter outperformed the market by only 2.5% a year, emphasizing that the quality of implementation is as important as the investment idea itself. In this paper, we establish the importance of trading costs for managed portfolio performance by documenting economically substantial heterogeneity, and more importantly, persistence in trading costs across institutional investors.

Our study contributes to the literature on the performance of financial intermediaries. Prior academic research has focused on the performance of money managers, such as mutual funds, hedge funds and institutional plan sponsors. However, there is little academic work examining the performance of another category of financial intermediaries, namely trading desks, responsible for trillions of dollars in executions each year. Since Jensen (1968), many of the tests in the performance measurement literature examine performance persistence: whether past performance is informative about future performance. In the context of mutual funds, recent studies (see, for example, Kacperczyk and Seru (2007), Bollen and Busse (2005), and Busse and Irvine (2006)) find strong evidence that funds can sustain relative performance beyond expenses or momentum over adjacent periods. This evidence on persistent performance by funds raises an important question regarding the sources of persistence. Most prior work

[1] For example, using institutional data provided by the Plexus Group, Chiyachantana, Jain, Jiang and Wood (2004) reports average trading costs of 41 basis points for 1997-98 and 31 basis points for 2001. Other related studies include Chan and Lakonishok (1995), Keim and Madhavan (1997), Jones and Lipson (2001), Conrad, Johnson and Wahal (2001) and Goldstein, Irvine, Kandel and Wiener (2008).

attributes some part of persistence to fund manager skill. However, Baks (2006) decomposes outperformance into manager and fund categories and reports that manager skill accounts for less than half of fund outperformance and that the fund is more important than the manager.

If managerial stock picking prowess is the primary driver then why would the fund be a source of relative performance? It is now recognized that trading costs have the ability to erode or eliminate the value added by money managers. Portfolio managers rely on the buy-side trading desks to implement their investment ideas. A trading desk can add value to an institution's portfolio by supplying expertise in transaction cost analysis. It is therefore natural to ask whether the execution process can be a source of persistence in institutional performance. Unfortunately, the information necessary to estimate institutional trading costs is difficult to obtain from publicly available sources. In particular, publicly available databases, such as NYSE's Trade and Quote (TAQ) database do not identify whether a trade was a buy or a sell or whether a trade represented all or part of an institutional investor's larger package of trades.

In this study, we examine a proprietary database of institutional investor equity transactions compiled by ANcerno Ltd. (formerly the Abel/Noser Corporation). The data contain approximately 35 million order tickets that are initiated by 664 institutional investors and facilitated by 1,137 brokerage firms over a seven-year period, 1999-2005, representing $22.9 trillion in trading volume. The database is distinctive in that it contains a complete history of each order ticket, each typically resulting in more than one execution, sent by an institutional investor to a broker. This history includes stock identifiers that help obtain relevant data from other sources, and more importantly for this study, codes that identify the institution and the broker associated with each ticket. The detailed transaction level ANcerno dataset seems particularly well suited for studying whether institutional trading desks can sustain relative performance over adjacent periods and contribute to fund performance persistence.

Our paper focuses on a literature that examines heterogeneity in transaction costs for specific groups of intermediaries. Linnainmaa (2007) uses Finnish data to argue for differences in execution costs across retail and institutional broker types. Conrad, Wahal and Johnson (2001) document the relation between soft-dollar arrangements and institutional trading cost. Keim and Madhavan (1997) and

Christoffersen, Keim and Musto (2006) show dispersion in trading costs of institutions and mutual funds. Yet, dispersion does not imply persistence. Furthermore, institutional execution is a joint production process that incorporates the decisions of both institutions and their brokers. Our paper complements this body of literature by using more extensive set of domestic trading data that allow us to integrate both institutional execution and broker execution into a single framework. We extend the literature on trading costs by testing for persistent trading skill and by identifying trading attributes associated with performance. To our knowledge, this is the first study to directly examine performance persistence of buy-side institutional desks and sell-side brokers.

We find that institutional trading desks can sustain relative performance over adjacent periods. Our measure of trading cost, the execution shortfall, compares the execution price with a benchmark price when the institutional trading desk sent the ticket to the broker. It reflects the bid-ask spread, the market impact and the drift in price while executing the order.[2] We sort institutional trading desks based on execution shortfall during the portfolio formation month and create quintile portfolios. We find that institutional trading desks with the lowest (highest) execution shortfall in the portfolio formation month continue to exhibit the lowest (highest) execution shortfall during the next four months. The results are similar when we control for the economic determinants of trading cost, such as ticket attributes, stock characteristics and market conditions. Remarkably, the best institutional trading desks exhibit a persistent pattern of *negative* execution shortfall, suggesting that the best traders help create positive (investment) alpha through their trading strategies.

We investigate several possible explanations for trading desk performance persistence. Trading desks are responsible for developing guidelines for broker selection and for establishing controls to monitor broker performance. We therefore examine whether some brokers can deliver better execution consistently over time. We find that brokers ranked as top performers during portfolio formation month continue to exhibit the lowest execution shortfall in subsequent months. These findings suggest that

[2] We do not consider explicit costs such as commissions in our transaction cost measure. However, we later consider commissions as one possible explanation for execution quality.

brokers exhibit significant heterogeneity in execution quality and that the top brokers can sustain their advantage over adjacent periods. The best brokers can execute trades with zero execution shortfall, which is particularly striking since our dataset contains the trades initiated by large investors.

We examine whether the persistence in institutional and broker performance is independent, or whether one effect subsumes the other effect. We find that there exist significant differences in execution cost across trading desks that are unique to the institution and not systematically related to the broker. Further, the combined effects of the institution and the broker are economically large. For example, the difference in execution cost between the top quintile institutions trading through top quintile brokers [top institution-broker pair] and the bottom quintile institutions trading through bottom quintile brokers [bottom institution-broker pair] is approximately 100 basis points, suggesting that trading cost persistence is large enough to significantly contribute to mutual fund performance persistence.[3] Our decomposition analysis indicates that almost half the difference in execution cost can be attributed to the trading desk's choice of brokers, emphasizing the importance of broker selection in the execution process.

We do not find support for the hypothesis that trading cost persistence is driven by the institution's investment style. Yet, we identify a set of trading decisions that are associated with performance. Institutions receiving poor executions specify low commission (or 'touch') execution venues, suggesting that they tend to focus on explicit trading costs. However, this choice is sub-optimal and can ultimately cost the institution considerably more in execution shortfall than the savings in commissions. Our evidence suggests that simple strategies such as concentrating order flow with fewer brokers help institutions receive better execution. Brokers who specialize by sectors or industries, generally boutique brokerage firms rather than generalists, tend to provide better executions. Higher explicit brokerage commissions is associated with better execution performance, which contrasts with findings in the mutual fund literature that higher explicit compensation to money managers (in the form of

[3] Recent studies estimate that the spread in fund performance between top and bottom quintile is around 3 percent to 6 percent per year (see Busse and Irvine (2006), Kacperczyk et al. (2006)). Assuming an average annual mutual fund turnover rate of 100 percent (see Edelen et al. (2007)), trading costs can significantly contribute to persistence in fund performance.

higher management fees) is associated with lower fund performance. Our findings also suggest that trading costs decline when the broker expends more effort in working the order. Well-capitalized brokers tend to provide significantly better execution, suggesting that their capital, and the ability to provide a direct counterparty for difficult to execute trades, represents a difficult to replicate competitive advantage.

Institutional investors account for a significant portion of equity ownership and an increasing percentage of daily trading volume in financial markets. As a consequence, understanding the determinants of institutional performance is of special interest to investors, money managers, and regulators. We document economically substantial heterogeneity in institutional trading costs and also persistence in relative performance across trading desks. We present evidence on the presence of skilled traders as well as their ability to create positive (investment) alpha and sustain out-performance over time. Since the investor's net realized returns depend on the implementation cost of investment ideas, our findings present new evidence on how the trading process can contribute to institutional performance. Because transaction cost savings can be substantial, we recommend that investment management firms implement trade management processes that assess the costs and quality of trades. From a regulatory perspective, the study should inform regulatory initiatives such as SEC Concept Release S7-12-03, which considers "whether mutual funds should be required to quantify and disclose to investors the amount of transactions costs they incur, include transaction costs in their expense ratios and fee tables, or provide additional quantitative or narrative disclosure about their transaction costs." Our evidence suggests that increased disclosure on mutual funds' trading costs can provide useful incremental information for investors' decision making process.

This paper is organized as follows. In Section 2, we describe the institutional trading process and review the literature on measuring trading costs of mutual funds. Execution cost measures and the sample selection are presented in Section 3. In Section 4, we report the results on performance of institutional trading desks. In Sections 5 and 6, we consider possible explanations for performance persistence. Section 7 discusses the possible contribution of the trading desk to fund performance. Section 8 summarizes the findings and concludes.

2. Background

2.1. The Institutional Trading Process

A typical order originates from the desk of a portfolio manager at a buy-side institution. Portfolio managers hand off the order with some instructions on trading horizon to the buy-side trading desk. The trading desk makes a set of choices to meet the best execution obligation, including which trading venues to use, whether to split the order over the trading horizon, which broker(s) to select and how much to allocate to each broker. The allocation to the broker, defined in our analysis as a ticket, may in turn result in several distinct trades, or executions, as the broker works the order.

The trading desk can supply expertise by implementing processes for measuring execution quality, developing broker selection guidelines and monitoring broker performance, offering advanced technological systems to access alternative trading venues such as dark pools, and selecting a strategy that best suits the fund manager's motive for the trade. For example, a portfolio manager who wishes to raise cash by doing a program trade, or a value manager trading on longer-term information, can be better served with passive trading strategies, such as limit orders (see Keim and Madhavan (1995)). In contrast, portfolio managers who trade on short-lived information, or index fund managers who try to replicate a benchmark index may be better served with aggressive trading strategies, such as market orders, to assure quick execution.[4] The trading problem is especially difficult for orders that are large relative to daily security trading volume. Large traders may choose to use the services of an upstairs broker or purchase liquidity from a dealer at a premium (see Madhavan and Cheng (1997)). More influential institutions could insist that their broker provide capital to facilitate their trades. In an increasing electronic marketplace, trading desks specialize in detecting pools of hidden liquidity (see Bessembinder, Panayides and Venkataraman (2009)) and building trading algorithms that respond quickly to market conditions.

[4] The evidence on the link between trader identity and order urgency is relatively weak. Keim and Madhavan (1995) find that institutional investors in their sample trade primarily using market orders and "show a surprisingly strong demand for immediacy, even in those institutions whose trades are based on relatively long-lived information. Consequently, it is rare that an order is not entirely filled." Similarly, Chiyachantana et al. (2004) report average fill rates for their sample of institutional orders exceeding 95% for all sample years. The ANcerno dataset does not provide information on fill rates for a ticket. Following Keim and Madhavan (1997), we do not assign a cost to any portion of the desired order that is not executed.

2.2. Measuring Execution Costs of Mutual Fund Trades

Prior research has recognized that trading cost can be a drag on managed portfolio performance (see, for example, Carhart (1997)). Since transaction data for mutual funds are not publicly available, the previous literature relating mutual fund performance and trading cost has relied predominantly on quarterly ownership data. A commonly used measure for trading cost is the mutual fund turnover, defined as the minimum of security purchases and sales over the quarter, scaled by average assets. The turnover measure makes the simplifying assumption that funds trade similar stocks and incur similar costs in executing their trades and is therefore a noisy proxy for trading cost.

Another measure, proposed by Grinblatt and Titman (1989) and implemented recently by Kacperczyk, Sialm and Zheng (2008), is based on the return gap between the reported quarterly fund return and the return on a hypothetical portfolio that invests in the previously disclosed fund holdings. As noted by Kacperczyk et al. (2008), the return gap is affected by a number of unobservable fund actions including security lending, timing of interim trades, IPO allocations, agency costs such as window dressing activities, trading costs and commissions, and investor externalities. While the return gap can gauge the aggregate impact of the unobservable actions on mutual fund performance, the authors note that it is impossible to clearly attribute its effect to any specific action.

Some studies, such as Wermers (2000), have estimated the execution cost of mutual funds using the regression coefficients from Keim and Madhavan (1997), who examine trading cost for a sample of institutions between 1991 and 1993. Edelen, Evans and Kadlec (2007) propose a new measure that combines changes in quarterly ownership data on a stock-by-stock basis with trading costs estimated for each stock from NYSE TAQ data. However, as acknowledged by these studies, their estimates significantly *understate* the heterogeneity in execution cost across mutual funds. This is because trading costs can vary significantly across institutions, reflecting differences in the skills across trading desks, or within a stock, reflecting time-varying liquidity conditions in a particular stock.[5]

[5] Consistent with previous studies, we observe in our sample that institutions exhibit significant difference in trading cost for stocks with similar characteristics.

Our study is distinguished from these studies and earlier work partly because we examine persistence in trading costs but also because we can estimate with greater precision the total trading costs, including costs of timing, price impact and commissions, associated with *each* institution. By analyzing detailed institutional trade-by-trade data, we are able to capture the heterogeneity in trading efficiency or skill across trading desks over time. Further, since the dataset contains the complete trading history for each institution, we can observe all trading activity, including all purchases and sales of the stock made within a quarter, which cannot be observed from changes in quarterly snapshots of fund holdings.

Prior research using the Plexus database has made important contributions to our understanding of institutional trading costs.[6] However, persistence in trading desk performance has not been established in the literature. This is because Plexus changes the anonymous institutional identifiers every month, thus making it difficult to track the performance of an institution over time. In contrast, ANcerno retains the unique identifier for an institution over time. The ANcerno database also offers significant advantages over the Plexus database in terms of its breadth and depth of institutional coverage as well as the length of the time period covered. One disadvantage of our data relative to Plexus is that ANcerno does not categorize institutions based on their investing strategy. As discussed later, we overcome this deficiency in the data by categorizing institutions on style attributes based on the characteristics of stocks they trade. Moreover, it is important to note that the focus of our investigation differs from related work in the literature. For example, we examine separately the role played by institutional-execution versus broker-execution in a single framework and establish separately persistence in buy-side and sell-side trading desk performance.

3. Execution Shortfall Measure and Descriptive Statistics of the Sample

3.1. Execution Shortfall Measure

Our measure of trading cost, the execution shortfall, compares the execution price of a ticket with the stock price when the trading desk sends the ticket to the broker. The choice of a pre-trade benchmark

[6] Important studies using the Plexus data include Edwards and Wagner (1993), Chan and Lakonishok (1995), Keim and Madhavan (1995, 1997), Jones and Lipson (2001), Conrad, Johnson and Wahal (2001), among others.

price follows prior literature and relies on the implementation shortfall approach described in Perold (1988).[7] We define execution shortfall for a ticket as follows:

$$Execution\ Shortfall(b,t) = [(P_1(b,t) - P_0(b,t)) / P_0(b,t)] * D(b,t) \qquad (1)$$

where $P_1(b,t)$ measures the value-weighted execution price of ticket 't', $P_0(b,t)$ is the price at the time when the broker 'b' receives the ticket, and $D(b,t)$ is a variable that equals 1 for a buy ticket and equals -1 for a sell ticket.

3.2. Sample Descriptive Statistics

We obtain data on institutional trades for the period from January 1, 1999 to December 31, 2005 from Ancerno Ltd. (formerly the Abel/Noser Corporation). ANcerno is a widely recognized consulting firm that works with institutional investors to monitor execution costs. ANcerno clients include pension plan sponsors such as CALPERS, the Commonwealth of Virginia, and the YMCA retirement fund, as well as money managers such as MFS (Massachusetts Financial Services), Putman Investments, Lazard Asset Management, and Fidelity. Previous academic studies using ANcerno data include Goldstein, Irvine, Kandel and Wiener (2008), Chemmanur, He and Hu (2009), and Lipson and Puckett (2007).

Summary statistics for ANcerno trade data are presented in Table 1. The sample contains a total of 664 institutions, responsible for approximately 35 million tickets and leading to 87 million trade executions.[8] For each execution, the database reports identity codes for the institution and the broker involved in each trade, the CUSIP and ticker for the stock, the stock price at placement time, date of execution, execution price, number of shares executed, whether the execution is a buy or sell, and the commissions paid. The institution's identity is restricted to protect the privacy of ANcerno clients; but the

[7] Some studies (see Berkowitz, Logue and Noser (1988), Hu (2005)) have argued that the execution price should be compared with the volume-weighted average price (VWAP), a popular benchmark among practitioners. Madhavan (2002) and Sofianos (2005) present a detailed discussion of VWAP strategies and the limitations of the VWAP benchmark. Among them, the VWAP can be influenced by the transaction that is being evaluated. Further, an execution may outperform the VWAP but in fact may be a poor execution because the broker has delayed the trade and the stock price has drifted away since the time when the broker received the ticket.

[8] As a point of comparison with studies using Plexus data, Edwards and Wagner (1993) examined 64,000 orders, Chan and Lakonishok (1995) examined 115,000 orders, and Keim and Madhavan (1997) examined 25,732 orders.

unique client code facilitates identification.[9] Conversations with ANcerno confirm that the database captures the complete history of all transactions of the portfolio managers.[10] Over the sample period, ANcerno institutional clients traded more than 755 billion shares, representing more than $22.9 trillion worth of stock trades. The institutions are responsible for 7.97% of total CRSP daily dollar volume during the 1999 to 2005 sample period.[11] Thus, while our data represent the trading activities of a subset of pension funds and money managers, they represent a significant fraction of total institutional trading volume.

We use stock and market data from the CRSP and TAQ databases to complement our analysis of the ANcerno trade data. We obtain the market capitalization, stock and market returns, daily volume and listing exchange from CRSP, and daily dollar order imbalance from TAQ. For a stock, the dollar order imbalance is defined as the daily buyer-initiated minus seller-initiated dollar volume of transactions scaled by the total dollar volume. TAQ trades are signed as buyer or seller-initiated using the Lee and Ready (1993) algorithm.

There are several notable time-series patterns in institutional trading observed in Table I, Panel B. The number of brokers and institutions in the database remains relatively constant. The number of stocks has declined, from 5,671 in 1999 to 4,237 in 2005, while volume has been steady, particularly since 2000 at over 5 million tickets. The average ticket size has declined from 24,088 in 1999 to 13,067 in 2005, with a significant decline in 2002 coinciding with decimalization. In the recent sample period, the ticket is broken up more frequently, as evidenced by the increase in the number of executions per ticket. The execution shortfall has declined, particularly since 2001, while the commissions increased markedly in

[9] In addition, the database provides summary execution information for each ticket, including the share-weighted execution price and the total shares executed. ANcerno provides a separate reference file for brokers that permits broker identification.

[10] ANcerno receives trading data directly from the Order Delivery System (ODS) of all money manager clients. The method of data delivery for pension plan sponsors is more heterogeneous. Our main findings are similar when we examine money managers and pension plan sponsors separately.

[11] We calculate the ratio of ANcerno trading volume to CRSP trading volume during each day of the sample period. We include only stocks with sharecode equal to 10 or 11 in our calculation. In addition, we divide all ANcerno trading volume by two, since each individual ANcerno client constitutes only one side of a trade. We believe this estimate represents a lower bound on the size of the ANcerno database.

2001 before declining in 2005. Sofianos (2001) remarks that the reduction in spreads that accompanied decimalization in 2001 made the NASDAQ zero commission business model untenable, and institutions began paying commissions on NASDAQ trades. This change is coincident with the increase in commission costs that we observe.

To minimize observations with errors, we impose the following screens: (1) Delete tickets with execution shortfall greater than an absolute value of 10 percent, (2) Delete tickets with ticket volume greater than the stock's CRSP volume on the execution date,[12] (3) Include common stocks listed on NYSE and NASDAQ, (4) Delete institutions with less than 100 tickets in a month for the institution analysis and delete brokers with less than 100 tickets in a month for the broker analysis, and (5) Delete all observations where the commission per share for a ticket is $0.10 or greater.

From Panel C of Table I, we note that the execution shortfall for sell tickets (39 basis points) exceeds those for buy tickets (13 basis points), consistent with Chiyachantana et al. (2004). This partly reflects the fact that the average sell order is larger than the average buy order. In Panel D, we report summary statistics based on CRSP market capitalization quintiles formed in the month prior to the trading month examined. Although the average ticket size for *Small* quintile stocks is only 8,932 shares, the average ticket represents a remarkable 33.8 percent of the stocks' daily trading volume. The average ticket size in *Large* quintile stocks exceeds 20,000 shares but represents only 1.2 percent of the stocks' daily volume. Clearly, tickets in *Small* quintile stocks are more difficult to execute, experiencing an average execution shortfall of 105 basis points. In contrast, the execution shortfall for *Large* quintile stocks is only 26 basis points.

4. Performance of institutional trading desks

4.1 Preliminary examination of persistence in institutional trading cost

Table II presents our initial examination of performance of institutional desks. For each institution, we calculate the execution shortfall for a ticket and then the volume weighted execution

[12] While this filter eliminates only 0.04% of all observations, we recognize that some tickets may correspond to executions in non-US markets. We have replicated the analysis without this filter and obtained similar results.

shortfall across all tickets for the month. We place institutions in quintile portfolios (1-best, 5-worst) based on monthly execution shortfall during the formation month (month *M*). Table II presents the time series average of equally weighted portfolio performance of institutions in month *M*.[13]

There is a large and significant difference of 139 basis points between the best and worst institutions in portfolio formation month. The best performing institutions execute trades with a negative execution cost of 41 basis points, while the worst performing institutions execute trades with an execution cost of 98 basis points. However, given the idiosyncratic nature of trading performance there are a myriad of market conditions that can affect the execution quality of particular trades. Thus, our test of trading desk performance merely uses the portfolio formation month as a benchmark for sorting trading desks into performance quintiles.

The key test of trading desk performance examines whether a quintile's relative performance persists into the future. In Table II, we report the average execution shortfall in future months *M+1* through *M+4* for institutions sorted into execution cost quintiles in month *M*. In month *M+1*, we note that institutions placed in (best performing) quintile 1 during month *M* report a negative execution cost of 7 basis points. In contrast, institutions placed in (worst performing) quintile 5 achieve an average execution cost of 62 basis points. We also note that the execution shortfall in month *M+1* increases monotonically from quintile 1 to quintile 5. The difference in month *M+1* performance between quintile 1 and quintile 5 is 69 basis points (t-statistic of difference = 57.07). In further support of performance persistence, we find that trends discussed above continue to be observed in month *M+2* through *M+4*, with the average Q1-Q5 difference in execution cost being 66, 65 and 63 basis points respectively (all statistically significant). Importantly, the difference in execution cost of approximately 65 basis points is also economically large.

As additional tests of performance persistence, we examine two statistics, the retention percentage (*Retention %*) and the percentile rank (*Percentile*). The *Retention %* for quintile 1 is the percentage of institutions ranked during month *M* in quintile 1 that continue to remain in quintile 1 when ranked on execution shortfall in a future month. *Retention %* helps examine the breadth of good and poor

[13] Value weighted construction produces similar results.

persistentence. As a benchmark, we expect the *Retention %* to be 20 percent for any quintile in a future month if performance rankings based on month *M* have no predictive power. However, from Table II, the *Retention %* in the extreme quintiles are as high as 46 percent, suggesting that the ranking based on month *M* is informative about future performance.

A second breadth measure, *Percentile* rank, reports the average percentile rank based on the execution shortfall estimated in future months for institutions ranked in a quintile during month *M*. By construction, the *Percentile* for quintile 1 (quintile 5) in month *M* is 10 (90). Under the null hypothesis that month *M* rankings have no predictive power, we would expect the *Percentile* for any institution quintile in future months to be 50. Alternatively, if the month *M* rankings have predictive power, we expect the *Percentile* for the best institutions in future months to be less than 50 (above average) and *Percentile* for the worst institutions to be greater than 50 (below average). We observe that, consistent with the alternative hypothesis of performance persistence, the *Percentile* for the best and the worst performing institutions deviate from 50 in the predicted directions.

4.2. Multivariate analysis of persistence in institutional trading cost

The evidence of institutional performance persistence, documented in the prior subsection, could arise if some institutions initiate easier to execute tickets than other institutions as a result of their distinct investment models. Therefore, it is important to control for ticket size and direction, as well as stock characteristics, such as market capitalization, stock price and trading volume. Further, institutional trading can be influenced by market conditions, such as stock volatility and short-term price trends (Griffin, Harris and Topaloglu (2003)), and by the market on which the stock trades (Huang and Stoll (1996)). Thus, cost comparisons across institutions or over time must control for the trade difficulty.

We estimate monthly, institution fixed-effect, regressions of execution shortfall on the economic determinants of trading cost. These variables include stock and market return volatility on the trading day; a *Buy* indicator variable that equals one if the ticket is a buy order and equals zero if it is a sell order; the order imbalance between buy and sell volume in the stock based on the prior trading day; a variable that interacts previous day order imbalance and the buy indicator; stock momentum, measured as the prior day's return; a variable that interacts momentum with the buy indicator; the stock's average daily volume over prior 30 trading days; stock market capitalization at the beginning of the month; the inverse of stock price; and ticket size normalized by the stock's average daily trading volume over prior 30 days. The regression model provides an estimate of the ticket's expected execution cost based on proxies for trade difficulty and serves as the benchmark for the performance measurement of trading desks.[14,15]

Our objective is to evaluate the performance of trading desks, holding the ticket, the stock, and the market condition measures at a common, economically relevant level. Following Bessembinder and Kaufman (1997), we therefore normalize every individual explanatory variable by deducting the sample mean of the explanatory variable for the month. Note that only the intercepts are affected by the normalization. In this specification, each institution's fixed-effect coefficient can be interpreted as the average execution cost for the institution in the month, evaluated at the monthly average of each explanatory variable. We term the institution coefficients as institution trading alphas, since the cross-sectional variation in institution coefficients can be attributed, at least in part, to the skill of the trading desk.

In Table III, Panel A, we report the average coefficient across 84 monthly regressions, the Fama-Macbeth t-statistics and p-values based on the time-series standard deviation of estimated coefficients, and the percentage of monthly regression coefficients with a positive sign. The estimated coefficients for the control variables are of the expected sign and statistically significant; the exception being the imbalance variables, which are not significant at the five percent level. Execution shortfall increases with stock volatility, reflecting the higher cost of a delayed trade in volatile markets, but declines with the

[14] To explore the possibility of a non-linear relation between the ticket size and execution shortfall, we estimate an alternative model using the log of normalized ticket size. The results are similar to those reported in the paper.

[15] We replicate the analysis using an execution shortfall measure that controls for the overall market movement on the ticket's execution day, and find similar results. Specifically, following Keim and Madhavan (1995), we use an adjusted execution shortfall measure, which deducts the daily return on the S&P 500 index from the ticket's execution shortfall. The adjusted measure is appropriate if trading desks can hedge their exposure to market movements using a futures contract or an ETF. Also, our findings are similar when we measure a ticket's execution shortfall based on the stock's opening price on the ticket's placement date instead of the stock price at the time when the broker receives the ticket. Detailed results are available from the authors.

stock's trading volume.[16] Trading against the previous day's momentum reduces execution cost, while trading with the momentum trend increases execution cost, which is consistent with Edwards and Wagner (1993)). Seller-initiated tickets are more expensive to complete than buyer-initiated tickets and, consistent with prior work, NYSE-listed stocks are cheaper to trade than NASDAQ stocks. Finally, execution shortfall increases with ticket size, suggesting that larger orders are more expensive to complete.

In Panel B of Table III, we report on the tests of persistence in trading alpha. The tests use the approach outlined for the unadjusted data in Table II. The most striking difference between the two tables is the reduction in the spread during the portfolio formation month between quintile 1 and quintile 5. This difference, which was 139 basis points in Table II, is reduced to 96 basis points in the regression framework. Despite the reduction in spread across quintile portfolios, our conclusions on the performance of trading desks are unchanged. In future month *M+1*, the difference in institutional performance between quintile 1 and quintile 5 is 62 basis points (t-statistic of difference = 69.4), which is similar to the 69 basis points reported in Table II. Persistence is also of similar magnitude for future months *M+2* through *M+4* (and also through *M+12*, see Figure 1, Panel A), suggesting that the conclusions from Table II are robust to controlling for differences in trade difficulty across institutions.

Even more striking is the finding that the coefficients on quintile 1 institutions are robustly *negative* in future months *M+1* through *M+4*, averaging between -12 and -15 basis points. A persistent pattern of negative execution shortfall suggests that the trading desks of the best institutions can help create positive (investment) alpha through their trading strategies. Recall that the mutual fund literature identifies a small subset of funds that exhibit persistent patterns in positive risk adjusted returns. Our findings imply that the trading desk can *contribute* to positive abnormal institutional performance. As discussed in Keim and Madhavan (1997), institutional desks can obtain negative trading costs by supplying liquidity or absorbing order imbalances.

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[16] The positive coefficient in trading cost regressions on market capitalization with control for trading volume is a common finding in empirical microstructure research (see, Stoll, 2000, for example). Prior research has attributed this relation to the high correlation between trading volume and market capitalization.

Our other measures of trading desk persistence are stronger in the regression framework than those reported in the univariate framework. The *Retention %* in the extreme quintile are as high as 50 percent and the *Percentile* for the best and the worst performing institutions deviate from 50 percent in the predicted direction. Overall, the results in Table III strongly suggest that past trading desk performance is informative about future trading desk performance.

5. Possible explanations of persistence

5.1. Evidence from brokers

We investigate several possible explanations for persistence in trading alpha. As discussed earlier, the trading desk is responsible for developing guidelines for broker selection and establishing controls to monitor broker performance. Brokers themselves may possess above average or below average ability to execute trades. We therefore examine whether some brokers can deliver better execution consistently over time. We repeat the regression analysis in Table III, Panel A with broker fixed effects rather than institution fixed effects. Following prior notation, we term the broker fixed effect as the broker's trading alpha. The control regression coefficients are presented in Table IV, Panel A and as before in Table III, Panel A, the only insignificant coefficients are associated with the imbalance variables. All other coefficients are of similar significance and sign.

Using the broker alpha estimates from Table IV, Panel A, we construct broker quintiles in portfolio formation month *M* by ranking the brokers each month by their trading alpha. The average trading alpha for a broker quintile over the sample period is presented in the portfolio formation month column of Table IV, Panel B. In the portfolio formation month, the spread between the top and bottom quintiles in the sample is 93 basis points.

More importantly, a significant part of this difference in execution cost is persistent (see Figure 1, Panel B). In future month *M+1* the difference between the best and worst performing brokers, at 28 basis points, is economically and statistically significant. The difference in broker performance persists in future months *M+2* through *M+4*, averaging between 28 and 25 basis points. Further, we find that the trading alpha for the best brokers (quintile 1) is insignificantly different from zero for future months *M+1* through *M+4*. The result that the best brokers in our sample can execute tickets with no price impact is particularly striking since we examine tickets initiated by large institutions. The latter likely reflects the skill of the brokerage firms in working the order and detecting pools of hidden liquidity.

Other tests also support the hypothesis that broker performance is persistent. Forty-two percent of the brokers placed in quintile 1 during month *M* are also ranked independently in the same quintile in future month *M+4*. Similarly, almost 33 percent of brokers ranked as the worst performers in month *M* continue to be ranked as the worst performers in month *M+4*. We find that the *Percentile* for the best brokers in future months is in the high-30s and the *Percentile* for worst brokers is in high 50s. These findings support that past broker performance is informative about future broker performance.

All of our persistence results are robust to the length of the periods examined. Specifically, the spread between the top and bottom performers is significant in future months *M+5* to *M+12*. In month *M+12*, the spread for institutional desks is 47 basis points (t-statistic=42.13) and for brokers is 20 basis points (t-statistic=13.75). The results up to month *M+12* are plotted in Figure 1 and detailed results are available from the authors.

5.2. The joint performance of institutional desks and brokers

Both institutional trading desks and brokers exhibit persistence in relative performance. The difference between the best and worst performers is economically large enough to have a considerable influence on measures of portfolio performance. We now examine whether the institutional and broker performance is independent, or conversely, if one drives the other. For example, if certain brokers are skilled at execution, then perhaps institutional clients of these brokers will tend to exhibit performance persistence. Similarly, if certain institutions are better traders, perhaps it is the case that institutions are skilled and they just tend to concentrate their trading with particular brokers.[17] Finally, it is possible that both specific brokers and institutions have superior trading skills.

[17] Goldstein et al. (2008) report that institutions tend to concentrate order flow with a few brokers. This concentration causes significant differences in the client lists of brokers and the broker lists of clients.

5.2.1. Analysis of Trading Volume Market Share

We examine the institution's order routing decisions to see whether the best institutions trade predominantly with the best brokers, and vice-versa. In Figure 2, Panel A, we plot the percentage of dollar trading volume routed by an institution quintile to each broker quintile, in Month *M*. Institution and broker quintile rankings are based on independent trading alpha estimates described earlier in Tables III.B and IV.B. Brokers ranked as average (quintile 3) are the largest in that they execute about 33 percent of the institutional volume. There is little variation in their market share across institution quintiles. The best performing institutions execute 39 percent of volume with above-average brokers (the top two quintiles) and 28 percent of volume with below-average brokers (the bottom two quintiles). In contrast, the worst performing institutions execute 33 percent of volume with above-average brokers and 37 percent of volume with below-average brokers. While broker selection can serve as a partial explanation for patterns in institutional performance, there is no evidence of clustering of institutions with certain broker types.

Similarly, broker performance may be a function of the trading skill of the institutional desk. Figure 2, Panel B presents the proportion of dollar trading volume for each broker quintile that is attributable to each institutional quintile. Institutions ranked as average (quintile 3) are the largest, accounting for about 31% to 40% of the order flow across broker quintiles. The best performing brokers receive 33% of their order flow from above-average institutions (the top two quintiles) and 30% of the order flow from below-average institutions (the bottom two quintiles). In contrast, the worst performing brokers receive *only* 14.5% of their order flow from above-average institutions and 53.5% of their order flow from below-average institutions. If certain institutions trade badly, then the brokers receiving order flow from these institutions will perform poorly. Clearly, the marked deviations in institutional order flow across broker performance quintiles observed in Figure 2, panel B suggests that broker performance can be assessed only after controlling for institution performance.

5.2.2. Evaluating independent patterns in institution and broker persistence

Trading performance is a joint production problem as it takes both a broker and an institutional desk to execute a ticket. We attempt to disentangle their relative contribution to trade performance by exploiting data on institution and broker codes at the individual ticket level. For each portfolio formation month, we calculate the institution trading alphas and sort them into quintiles. For each month, we also (independently) calculate broker trading alphas and sort them into quintiles. Thus, for each portfolio formation month, each ticket is associated with an institution quintile rank and a broker quintile rank.

We then use the institution and broker quintile designations to assign each ticket to one of 25 quintile intersection (5×5) portfolios. With dummy variables representing each of the 25 portfolios, we estimate the trading alpha for each of the 25 portfolios in the portfolio formation month and in months $M+1$ through $M+4$ separately. As before, the estimation in months $M+1$ through $M+4$ uses portfolios formed on the basis of broker and institution rankings in month M, and the same control variables as those in Tables III, A and IV, A.

We use our 25 formation-month portfolios to address the joint production problem in two complementary ways. First, in Table V, Panel A, note that each broker quintile is associated with five performance-ranked institution portfolios. To assess evidence on institutional persistence after controlling for broker effects, we examine institutional persistence *within* each broker quintile. That is, for each broker quintile, we report the trading alphas of (a) the portfolio of the best-performing institutions, (b) the portfolio of worst-performing institutions, and (c) the difference between the two portfolios (and the t-statistics of difference), during portfolio formation month M and future months $M+1$ through $M+4$.

The general conclusion from Table V, Panel A is that the persistence in institutional trading costs can be observed after controlling for broker effects. Although the largest performance differential between the best and worst institutional quintiles is observed among the best performing brokers (72 basis points in month $M+1$), note that institutional performance differentials do not monotonically deteriorate with broker quality. The second largest institutional performance difference occurs in broker quintile 5, the worst performing brokers.

Conversely, it may be true that certain institutions possess execution skills and when these particular institutions concentrate their trading with certain brokers they produce the patterns in broker performance as observed in Table IV, Panel B. So, can broker persistence be driven by institution-specific characteristics, such as trading style? To examine this hypothesis, we reverse the analysis in Panel A. For each institutional quintile, we calculate the performance differential between the best and worst performing brokers in portfolio formation month and future months. Analysis of these results allows us to determine whether broker performance differences are systematically related to institutional style.

The results in Panel B indicate that broker performance differences are again the largest for tickets received from the best performing institutions, ranging from 31 to 35 basis points in future months *M+1* to *M+4*. Similar to Panel A, the second largest broker differences are observed in orders received from the worst performing institutions. Yet again, we cannot support the theory that broker performance differences are due solely to institutional effects, such as trading style. Across institutional quintiles, we observe persistent difference in broker performance of at least 20 basis points across all future months.[18] Thus, past broker performance is informative about future performance, suggesting that institutions should consider past performance when selecting brokers. We provide some empirical evidence consistent with this behavior in Section 6.4.

Figure 3 presents a graphical representation of the execution shortfall across the broker-institution portfolios in month *M+1*. Several observations are noteworthy. Within broker quintiles, there exist significant differences in trading cost across trading desks that are unique to the institutions. Similarly, within institutional quintiles, we observe a monotonic improvement in performance from the worst to the best performing brokers in future month *M+1*. From this evidence, we conclude that both specific institutions and brokers have superior (or inferior) trading skill and this skill is predictable based on past performance. Importantly, the combined effects of the institution and broker are economically large. For

[18] As a robustness check, we examine whether our findings are sensitive to the research design of the 25 formation-month portfolios. We test for broker persistence in an alternative fixed effects specification where an institution specific indicator variable, which equals one for an institution's ticket and equals zero otherwise, is included in the regression along with individual broker fixed effects. This specification controls for an institution's trading style and examines broker performance *within* an institution. The difference between the best and worst brokers is 21 basis point (t-statistics=16.33) in month *M+1* and 18 basis points (t-statistic=14.06) in month *M+4*. Similarly, we find that institutional desk persistence results are robust in a broker-specific indicator variable specification. For the sake of brevity, the results are not reported in the tables but are available from the authors.

example, the difference in execution cost between the top institution-broker pair and the bottom institution-broker pair is 97 basis points.

5.3. Performance Attribution

We next perform a trading alpha attribution analysis that is similar in spirit to the decomposition of return alpha into stock selection and market timing components. In this case, the 97 basis point difference between the top institution-broker pair and the bottom institution-broker pair reported in Figure 3 is split into two components - broker selection and institutional skill. Our attribution analysis is based on two simplifying assumptions: (1) brokers (institutions) placed in a quintile have similar trading skills but trading skills can vary across quintiles, and (2) a broker provides similar execution (or expends similar effort) for all institutions, thus abstracting from agency explanation for broker performance.

Table VI reports the trading alpha and the broker market share for institutions in month *M+1*. Column (1) of Table VI presents a hypothetical "most skilled" Quintile 1 institution with perfect foresight that routes 100 percent of its trades to the best brokers. In contrast, the average Quintile 1 institution routes only 13.6% of its trades to the best brokers. Similarly, column (4) presents a hypothetical "least skilled" Quintile 5 institution with poor foresight that routes 100 percent of its trades to the worst brokers. In contrast, the average Quintile 5 institution routes only 11.7% of its trades to the worst brokers. As discussed above, the trading alpha difference between the hypothetical "most skilled" and "least skilled" institution is (0.551% - (-0.416%) =) 0.97%. Columns (2) and (3) of Table VI present the trading alpha and broker market share for the average Quintile 1 and Quintile 5 institutions, respectively, across all broker quintiles based on data during the sample period. Note that the trading alpha by broker quintiles in columns (1) and (2) (and also, columns (3) and (4)) are identical, reflecting that institutions within a quintile are equally skilled and receive similar executions from a broker.

The two assumptions allow for the following decomposition of observed trading costs. We note that the "most skilled" institution (column 1) obtains a lower trading cost than the typical Quintile 1 institution (column 2) and this reduction in trading cost of (-0.136% - (-0.416) =) 0.280% can be solely attributed to broker selection, i.e., the decision of the "most skilled" institution to route 100% of its trades to the best brokers. Similarly, the difference in trading cost between the "least skilled" institution (column 4) and a typical Quintile 5 institution (column 3) is (0.551% – 0.427% =) 0.124%.[19] These two differences attribute 0.404% of the 0.97% difference in trading alpha to broker selection.

The residual difference of 0.566% can be attributed to institutional skill. From columns (2) and (3), we observe that Quintile 1 institutions obtain significantly lower trading alpha than Quintile 5 institutions for each broker quintile. For example, for trades routed to best brokers, the trading alpha for Quintile 1 and Quintile 5 institutions are -0.416% and 0.300%, respectively. This difference in trading alpha in columns (2) and (3), aggregated across broker quintiles based on the market share of brokers, is estimated to be 0.566% and represents institutional skill.[20] Thus, we attribute slightly less than half of the Figure 3 outperformance to the trading desk's decisions regarding broker selection and the remaining outperformance to institutional skill.

5.4. Can investment style explain institutional persistence?

Although certain institutions consistently obtain poor executions, the institutions may not violate their fiduciary Best Execution obligations if their approach reflects a trading style that realizes the maximum value of the firm's investment ideas. For example, a fund manager who trades on short-term momentum or information would choose aggressive strategies that incur high execution cost but enhance portfolio alpha. The *5×5* portfolio approach detailed in Section 5.3 controls for the effect of the institution's style on broker persistence but not on trading desk persistence. Is any trading desk persistence driven by the institutional style?

Information advantages are perishable and institutions wishing to exploit such advantages must trade accordingly. Private information is unobservable, but will eventually be revealed to the market.

[19] The average trading alphas for Quintile 1 (-0.136%) and Quintile 5 (0.427) institutions differ slightly from those reported in Table III, Panel B. These differences stem from the added restriction that both institutions and brokers must trade at least 100 tickets to be in the sample for Table VI. In Table III only the institutions need to meet the 100 tickets criteria.

[20] Our objective is to present a simplified framework for attributing performance to decisions made by a trading desk. We note that the hypothetical "most skilled" and "least skilled" institutions do not exist in our sample.

Thus, to examine whether poorly performing institutions may possess informational advantages that could lead to trading underperformance, we examine price patterns observed subsequent to a ticket's execution (post-trade price drift), defined as:

$$\textit{Post Trade Price Drift}\ (b,t) = [(P_{close}(t) - P_1(b,t)) / P_1(b,t)] \; * D(b,t), \qquad (2)$$

where $P_{close}(t)$ is the stock's closing price on the day after the day of ticket execution.

Keim and Madhavan (1997) use Plexus-defined investment styles of institutions to differentiate between patient and impatient traders. Similar information can be obtained by examining the price movements subsequent to a ticket, as the price drift estimates the opportunity cost to the institution of failing to execute in a timely fashion. If the institution's investment style demands urgency in executing the ticket, the post-trade price drift should be observed in the direction of the ticket. Therefore, if persistence can be explained by investment style, we expect the poorly performing institutions to be impatient traders, with large price movements subsequent to the ticket.

In Figure 4, we report the patterns in post-trade price drift in Month *M+1*. Within the top three broker quintiles (quintiles 1 to 3), the difference in post-trade price drift between the best and worst performing institutions is not significant. For broker quintile 4 and 5, the difference is statistically significant but inconsistent with the investment style hypothesis, as the poorly performing institutions exhibit smaller post-trade price drift than the best performing institutions. Thus, we fail to find empirical support for the hypothesis that execution urgency, arising from an institution's investment style, can explain persistence in trading cost.

As an alternative test for investment style effects, we categorize institutions into investment style groups based on the stocks that they have bought or sold during the sample period. We measure investment style using standard measures of fund style: market capitalization, the book-to-market (BM) ratio (calculated similar to Fama and French (1993)) and the six-month return momentum. We calculate the style characteristics for each stock in each month. Each ticket in the ANcerno database is merged with the style characteristics for the stock estimated in the month prior to the transaction month. For each institution in each month, we calculate the weighted average market capitalization, BM ratio, and return momentum based on the institution's tickets, where the weights are based on ticket size. In each month, institutions are classified as small or large cap, growth or value investment style, and low or high momentum based on whether, on average, the institution ranks above or below the median value for the particular style criterion.

If investment style can explain persistence, we expect that evidence on trading cost persistence within an investment style should be weak. In contrast, within each investment style, we find that trading desks sustain relative performance over time. For example, within institutions classified as "Value" style, the best institutions ranked during the portfolio formation month outperform the worst institutions in month *M+1* (*M+4*) by 60 (54) basis points. Similarly, within institutions classified as "Growth" style, the best institutions ranked during the portfolio formation month outperform the worst institutions in month *M+1* (*M+4*) by 57 (50) basis points. Our results do not support the investment style explanation for trading cost persistence, as persistence continues to exist after controlling for style.[21]

6. Determinants of Performance

What could account for persistent differences in trading cost across institutional desks? One possible explanation is that different institutional desks trade different stocks, some of which are more difficult to execute than others. However, our control regressions provide reasonable controls for stock characteristics, ticket attributes and market conditions that affect trading cost.[22] We also show above that our results are not driven by investment style.

A second explanation is that some institutions pay higher commissions on their trades and receive superior execution from their brokers. The ANcerno data provides information on brokerage commission

[21] We find similar results for the other style classifications. These results are not reported in the tables and are available from the authors.
[22] As a robustness check, we run the persistence analysis separately for stocks classified as large cap (size quintile 4 and 5) and small cap and find similar results for both groups. For small cap stocks in month *M+1*, the performance difference for institutional desk quintiles is 66 basis points and for broker quintiles is 25 basis points. Our results are similar when we construct decile (instead of quintile) portfolios. In month *M+1* (*M+4*), the difference between the best and the worst institution deciles and the best and the worst broker deciles are 84 (74) basis points and 38 (32) basis points, respectively. Results are also robust when we perform the persistence analysis before and after decimalization in 2001 for NYSE and NASDAQ stocks.

associated with each ticket. In Figure 5, we plot brokerage commissions in basis points, by quintile intersection (*5×5*) portfolios, formed during portfolio formation month (similar to Table V). Several important patterns are observed in Figure 5. Within any institutional quintile, we observe that the pattern in commissions across broker quintiles has a U-shape. If commission payments drive brokers to perform better, we expect commissions to decline monotonically from the top-performing to the bottom-performing broker. The commission patterns are not consistent with this explanation. Neither does the evidence support the explanation that broker incentive is driven by soft dollar arrangements between institutions and brokerage firms. Conrad, Johnson and Wahal (2001) show that soft dollar brokers provide worse executions relative to other brokers but also charge more commission than other brokers. But, from Figure 5, we see that quintile 5 brokers receive the same (not higher) commissions as other groups and the difference in commissions between top and bottom brokers is not significant for any institutional quintile.[23] Moreover, we observe performance persistence for both good and bad brokers.

The patterns suggest that the commission paid by the institution depend on the service received from the brokers. Within broker quintiles, the commissions decline monotonically from top to bottom institution quintiles (t-statistics exceed two in all broker quintiles). If commissions reflect the broker's effort, one explanation for these institutional patterns is the institution's preference for low 'touch' versus high 'touch' executions. Goldstein, Irvine, Kandel and Weiner (2008) report that, in response to ECN competition, full-service brokers now provide a full range of services ranging from low commission (or 'touch') executions such as direct access, dark pools and smart routers to high commission executions such as a sales team working an order or the dealer posting their own capital to facilitate the trade. From Figure 5, it appears that bottom-performing institutions specify low touch execution venues, perhaps reflecting a focus on explicit costs (commissions). Our evidence suggests these alternatives can ultimately cost institutions considerably more in execution shortfall than the explicit savings in commissions.

[23] A possible explanation is that soft dollars could be more directly associated with particular types of brokers during the mid-1990's period examined by Conrad, Johnson and Wahal (2001). Such a classification is more difficult in recent periods as the majority of brokers offer multiple commission contracts (Goldstein et al. (2008)).

A third explanation for differences in institutional performance is focused more on economic incentives and that skill in execution is partly determined by broker effort. The largest institutions are important clients generating large total revenues for the broker. Anecdotally, large institutions such as T. Rowe Price and Fidelity are known to punish brokers by withholding business if they feel the broker is leaking information about their trading patterns to the market. Brokers could put up more of their own capital to lower the execution costs of large clients, or brokers could expend greater effort in searching for low-cost counterparties, actions that suggest large institutions would receive better execution.

6.1. Cross-sectional regression of institutional performance

To test these ideas, we regress the trading alpha observed for the institution during the portfolio formation month *M* (i.e., institutional effects from Table III) on a set of explanatory variables that represent the trading decisions made by the trading desk. In contrast, note that the majority of explanatory variables in Table III, panel A, represent factors that are outside the control of the trading desk.

In Table VII, we report the average coefficients across the 84 monthly regressions and the Fama-Macbeth t-statistics and p-values. Consistent with Figure 5, we find that the coefficient on the institution's commissions is negative, suggesting that higher explicit brokerage compensation is associated with better execution. This is an interesting contrast to findings in the mutual fund literature that higher explicit compensation to money managers (in the form of higher management fees) is associated with lower fund performance. As expected, the coefficient on average ticket size is positive, suggesting that institutions executing larger tickets incur higher execution shortfalls on average. The variable *Herfindahl-I*, calculated as an institutions' monthly Herfindahl index of trading volume market share across brokers, measures the manner in which an institution routes orders to brokers. The significantly negative coefficient on *Herfindahl-I* suggests that institutions that concentrate trading with fewer brokers receive better execution. Since the institution's identity is unknown, we proxy for institution size based on the dollar volume of the institution's monthly transactions, and form quintile portfolios. Consistent with a size effect, we find that larger institutional desks have lower trading costs.

6.2. Cross-sectional regression of broker performance

In this section, we examine trading decisions that are systematically associated with broker performance. The second column in Table VII presents several variables that reliably predict performance differences across brokers. The results for average commissions and the average ticket size are similar to those observed in the institutional regressions. The number of executions per ticket is negatively related to broker trading alpha, implying that trading costs decline when the broker expends more effort in working the ticket. To capture the extent of broker specialization by industry or sector, we estimate the variable *Herfindahl-B*, a brokers' Herfindahl index of the trading volume market share across Fama-French industry groups. The negative coefficient on *Herfindahl-B* suggests that brokers who specialize in sectors or industries obtain better execution. [24] Specialization by industry allows brokers to observe order flow in related stocks and this information can provide a comparative advantage in executions.

Larger brokers have access to greater networks of counterparties than smaller brokers (Onaran (2007)). They may also be able to purchase the services of highly-skilled traders. Yet larger brokers have more clients and it is not clear how these resources would be allocated to particular clients. Small brokers may expend greater effort and secure superior execution for particular clients because these clients are important to them. This argument confounds a simple relationship between broker size and performance.

We gathered annual data on broker Capital from the Financial Industry Regulatory Association (FINRA) to identify bulge bracket brokers (*Bulge broker*) as those most likely to have capital available to facilitate their clients' execution. These seven brokers are capitalized with at least twice as much available capital as their nearest competitors with capital ranging from a minimum of $18 billion for Bear Stearns in 1999 to a maximum of $150 billion for Merrill Lynch in 2005.[25] The best capitalized brokers have

[24] Brokers can differ in their degree of specialization. At one extreme, the generalist brokers offer execution services in a wide variety of stocks and serve as a convenient one-stop shop for clients. At the other extreme, boutique brokers such as Freeman, Billings and Ramsey, specialize in executing stocks in select industries. *Herfindahl-B* is a proxy for broker specialization by industry. We thank Tim McCormick for suggesting this line of investigation.
[25] Broker capital is defined as shareholder's equity plus subordinated debt. The 7 bulge bracket brokers are Merrill Lynch, Goldman Sachs, Morgan Stanley, Citigroup, Lehman Brothers, Bear Stearns and, after their 2000 merger with DLJ, Credit Suisse First Boston.

significantly better performance suggesting that their capital, and the ability to provide a direct counterparty for difficult to execute trades, represents a difficult to replicate competitive advantage.[26]

6.3. Is the institution's choice of broker sensitive to past execution quality?

If some brokers are persistently bad, then why do they survive? There is a similar debate in the mutual fund literature on why poorly performing index funds or money market funds survive (Elton, Gruber and Busse (2004)). In the context of our study, the worst performing brokers can survive because some institutions are either performance-insensitive or face substantial information gathering costs. Institutional barriers to order flow (for example, endowments mandated to trade through custody banks), capacity limitations at good brokerage houses, or agency conflicts can also serve as explanations.[27] Yet another explanation is that institutions use order flow to purchase a package of non-execution related services, which would otherwise be paid for explicitly.

We examine whether the worst performing brokers get penalized and the best performing brokers get rewarded in future periods. For each institution, we identify the ten brokers receiving the highest trading volume from an institution over a six-month ranking period (top 10 brokers). We relate a broker's execution shortfall with its ability to retain a top 10 status during the next six months (the observation period). The best performing brokers during the ranking period have a 66 percent chance of retaining the top 10 status in the observation period. In contrast, the worst performing brokers have a 60 percent chance of retaining their top 10 status (p-value of difference < 0.01). We also examine the propensity for a broker to leverage execution performance into top 10 status in the observation period. The best (worst) performing brokers exhibit a likelihood of 6.49 percent (6 percent) of being elevated to an institution's top 10 in the observation period (p-value of difference < 0.01).

Finally, we examine the change in market share of brokers from ranking to observation period. We see an increase in market share, from 12.95 to 13.32 percent for top broker quintile and from 22.86 to

[26] However, we note that the negative relation between broker capital and trading cost is not monotonic throughout our broker sample as several lightly capitalized brokers also have superior execution performance.
[27] For example, the Securities and Exchange Commission fined Fidelity investments $8 million in March 2008 because Fidelity had directed trading business to brokerages that enticed Fidelity traders with gifts but not necessarily the best service. The case also led to an industry wide probe of gift-giving practices.

23.32 percent for broker quintile 2. In contrast, we see a decrease in market share, from 25.12 to 24.78 percent for broker quintile 4, and from 14.38 to 13.97 percent for bottom broker quintile. Although we examine a relatively short window, we find that institutions are sensitive to the past performance of brokers.[28] We conclude that execution costs do provide a competitive advantage to brokers. However, these forces are weak and the worst performing brokers lose market share rather slowly.

7. Discussion

Our evidence on the linkage between transaction costs and fund performance is indirect.[29] Nonetheless, trade executions represent a necessary expense associated with the implementation of investment ideas, and consequently, investment firms should be concerned about execution quality. We show that differences in institutional trading costs are substantial and persistent, implying that the cumulative impact of trading costs can dramatically affect the returns to a long-term investor in a fund. Suppose, for example, the mutual fund can reduce transactions cost by 62 basis points (the average difference between the best and the worst performing institutional quintiles) and has an annual turnover rate approaching 100 percent (which is the average mutual fund turnover rate as per Edelen et al. (2007)), the mutual fund can add an incremental 62 basis points to the fund's annual return. Importantly, since the mutual fund can sustain the relative (out-) performance over adjacent periods, an attention to trade execution can move the mutual fund several notches up the closely-clustered mutual funds rankings and help maintain the relative out-performance over time.

Further, we note that the cumulative dollar impact of trading desk decisions such as broker selection is large – an approximate calculation suggests that the annual trading cost reductions exceed $1 billion if institutions route order flow to the best performing brokers instead of the poorly performing

[28] The results are consistent with those reported by Boehmer, Jennings and Wei (2007), who examine the impact on order flow of SEC Rule 11Ac1-5 (Dash 5 reports), which mandates U.S. market centers to publish a broad set of standardized execution-quality metrics each month.

[29] Because ANcerno restricts the institutions identity to protect the privacy of its clients, we are limited in our ability to obtain fund returns from mutual fund databases.

brokers.[30] While this estimate is no doubt imprecise, the magnitude of the estimate emphasizes that broker selection based on past performance represents an important dimension of the fund's fiduciary obligation.

8. Conclusion

We contribute to the literature on the performance of institutional trading desks, an important category of financial intermediaries who are responsible for trillions of dollars in trade executions each year. We examine institutional equity transactions using data provided by ANcerno Corporation, a consulting firm that works with institutional investors to monitor their equity trading costs. Our main finding is that institutional trading desks can sustain relative performance over adjacent periods. The results support the existence of skilled traders who can help create positive (investment) alpha through their trading activities. We also find that some brokers can deliver better executions over time and that the combined effects of the institutional desk and the broker are large. We identify a set of trading decisions that are related to execution performance.

This study is also of interest to money managers, trading desks, regulators, and investors. Our evidence on the presence of skilled traders and their ability to sustain superior performance helps articulate the contribution of the trading process to investment performance. Best execution has been the subject of recent regulatory attention under U.S. Regulation National Market System (Reg NMS) and European Union's Markets in Financial Instruments Directive (MiFID). In defining Best Execution, regulators in the U.S. have emphasized the fiduciary duty of brokers and fund managers to obtain the best value for the investment decision.[31] Our results suggest that broker selection based on past trading performance is an important dimension of the money manager's fiduciary obligation. However, because

[30] A worst performing broker in our sample executes roughly $700 million each month, or $8.4 billion annually. In a typical month, the worst broker quintile has approximately 50 brokers. Thus, brokers in the bottom quintile execute roughly $420 billion each year. In Table IV, Panel B, we estimate trading cost difference between the best and the worst broker quintiles of approximately 28 basis points. If institutions route orders to the best brokers instead of the worst brokers, the estimated trading cost reduction is $1.18 billion. A similar approach can be used to estimate dollar amounts for other broker quintiles. Moreover, the dollar estimates understate the importance of broker selection since our sample contains (a) only a subset of institutions, and (b) institutions that are sensitive to execution quality.

[31] FINRA 2320(a) states "The Best Execution Rule require a member, in any transaction for or with a customer, to use reasonable diligence to ascertain the best inter-dealer market for a security and to buy or sell in such a market so that the resultant price to the customer is as favorable as possible under prevailing market conditions."

brokers provide a package of non-execution related services to institutions (such as prime brokerage services, IPO allocations, and research) and we have no way of measuring these potentially offsetting benefits, it is very difficult in reality to measure Best Execution. While our findings suggest that some institutions consistently obtain poor executions and can benefit from better rules for broker selection, we cannot necessarily conclude that these decisions violate their fiduciary obligation. We believe that increased disclosure of the institution's portfolio transaction costs and the trade management processes will provide meaningful information to fund investors.

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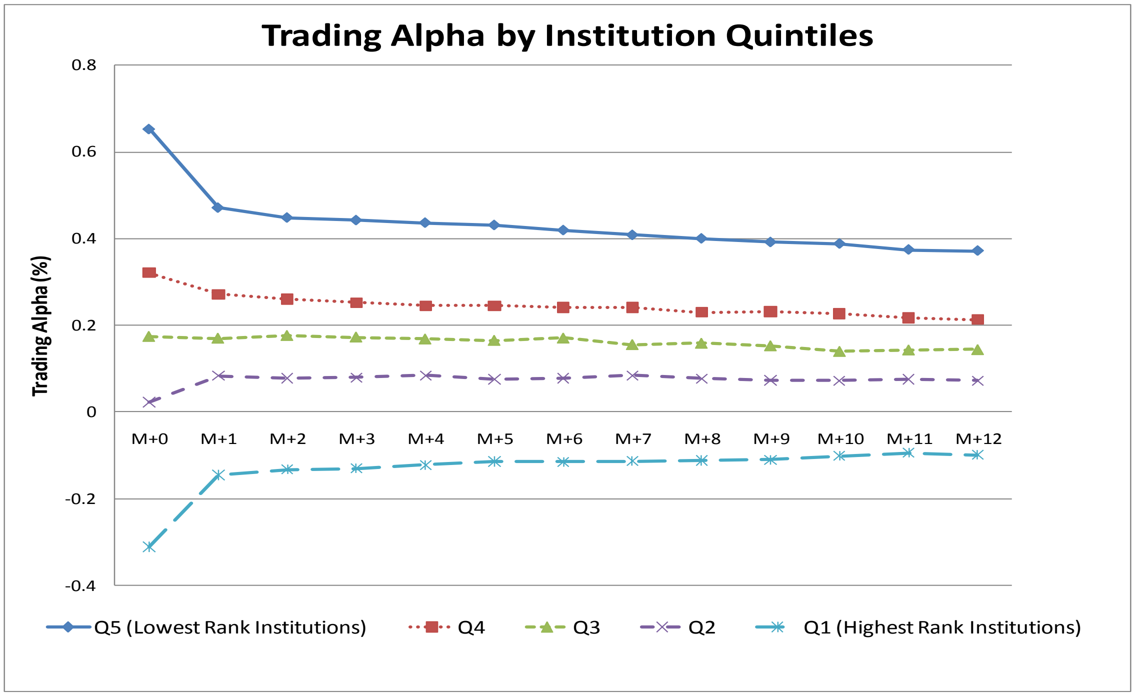
Figure 1: Institutional and Broker Trading Alphas

Figure 1 presents the monthly time series of Trading Alphas (in percent), by quintiles formed in portfolio formation month, for institutional trading desks (Panel A) and brokers (Panel B). The estimates are obtained from analyses similar to those presented in Tables III B and IV B.

Panel A



Panel B

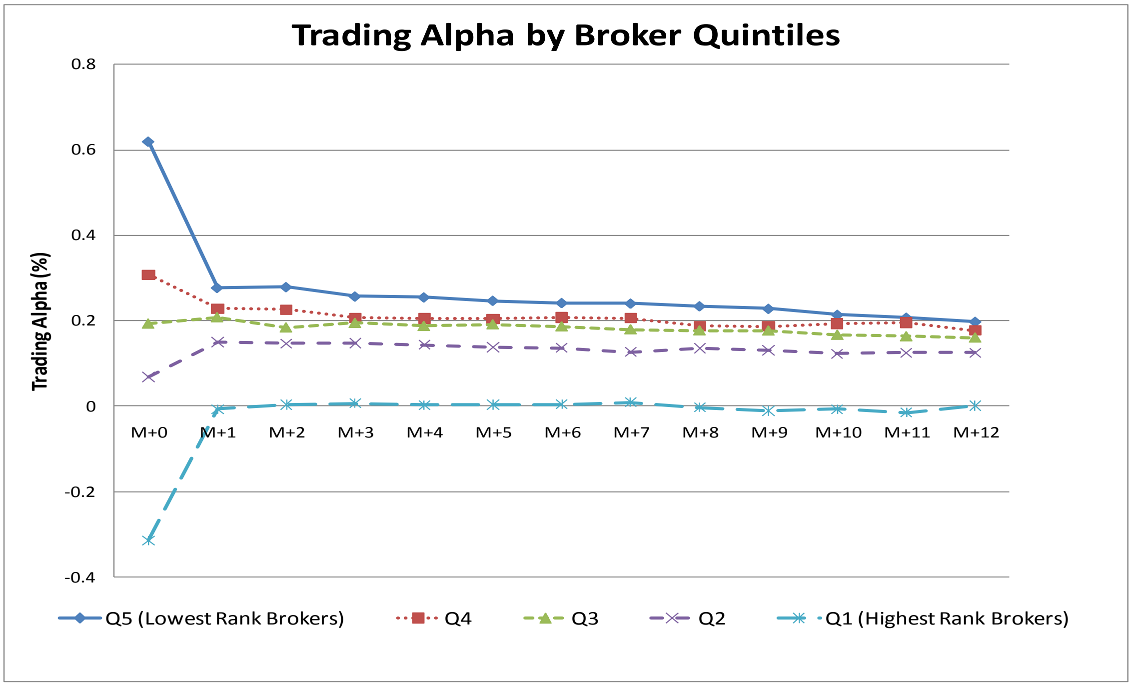
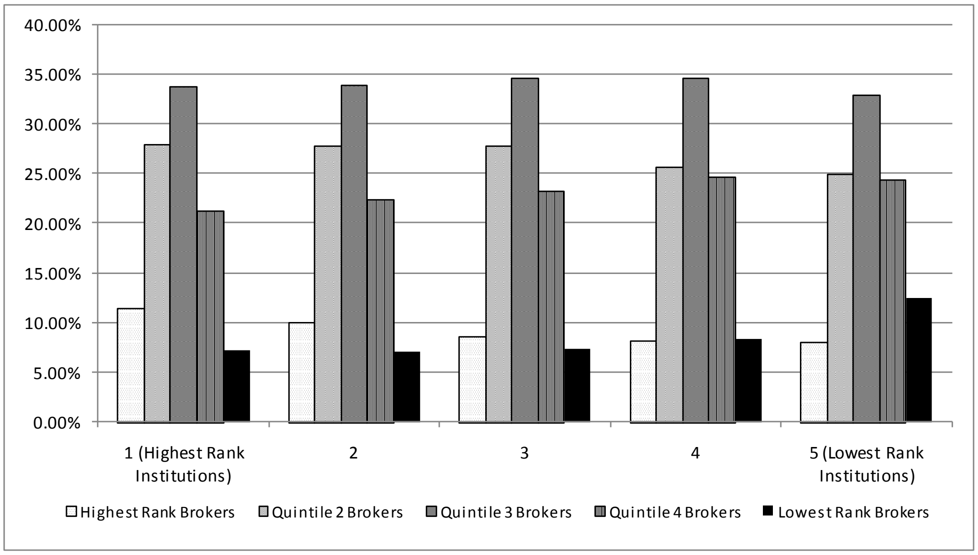


Figure 2: Trading Volume Market Share

Figure 2, Panel A presents the proportion of dollar trading volume routed by an institution quintile to each broker quintile. Panel B presents the proportion of dollar trading volume of each broker quintile that is attributable to each institutional client quintile. Institutional and Broker quintile rankings are based on independent trading alpha estimates described in Tables III B and IV B. Rankings as well as the dollar volume are measured contemporaneously.

A. Trading Volume Market Share of Institutions, by Broker Quintiles



B. Trading Volume Market Share of Brokers, by Institution Quintiles

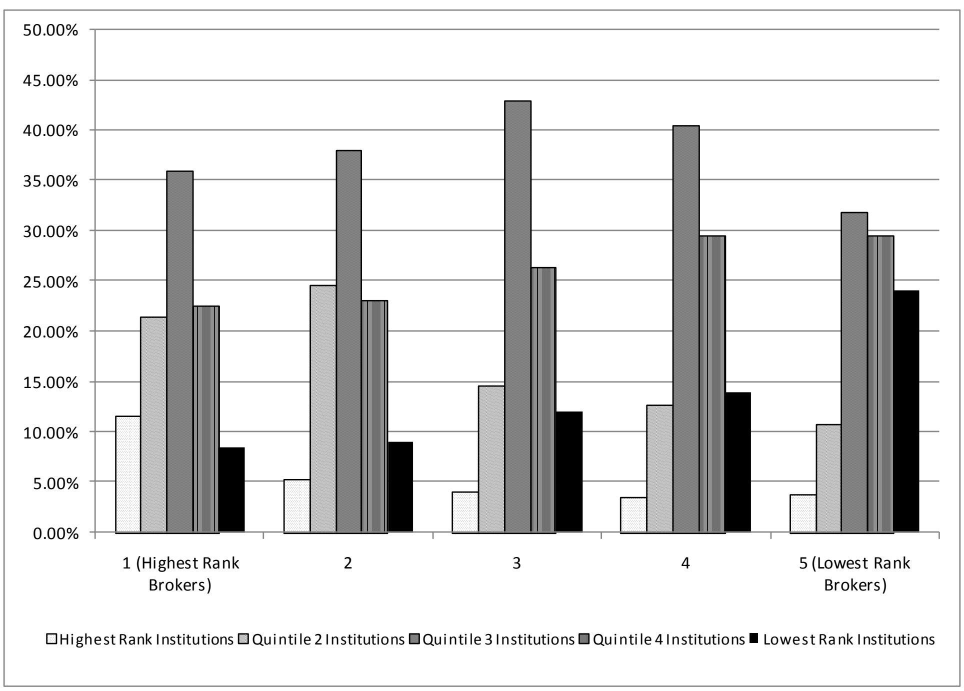


Figure 3

Trading Alpha, by Broker and Institution Quintiles, in Month M+1.

Figure 3 presents results for Trading Alpha (in percent) by Broker and Institution Quintile. For each month we first run monthly cross-sectional regressions separately (similar to Tables III B and IV B) using institution and broker dummy variables. Next, we use the rankings associated with each broker and institution in each month and assign each broker-institution combination into one of 25 categories. Then for each month, we estimate regressions using the execution shortfall as the dependent variable, and the control variables described earlier as well as the 25 broker-institution combination dummies as the independent variables (this specification excludes individual broker and institution dummy variables). We use each month's broker-institution combination ranking in month *M* to estimate a similar regression for the next month. Our methodology produces 25 coefficient estimates (that represent all possible institution-broker rank combinations) for the formation month (month *M*) and the subsequent month (month *M+1*). We report the coefficients estimated for the subsequent month for all 25 fractile categories in Figure 3.

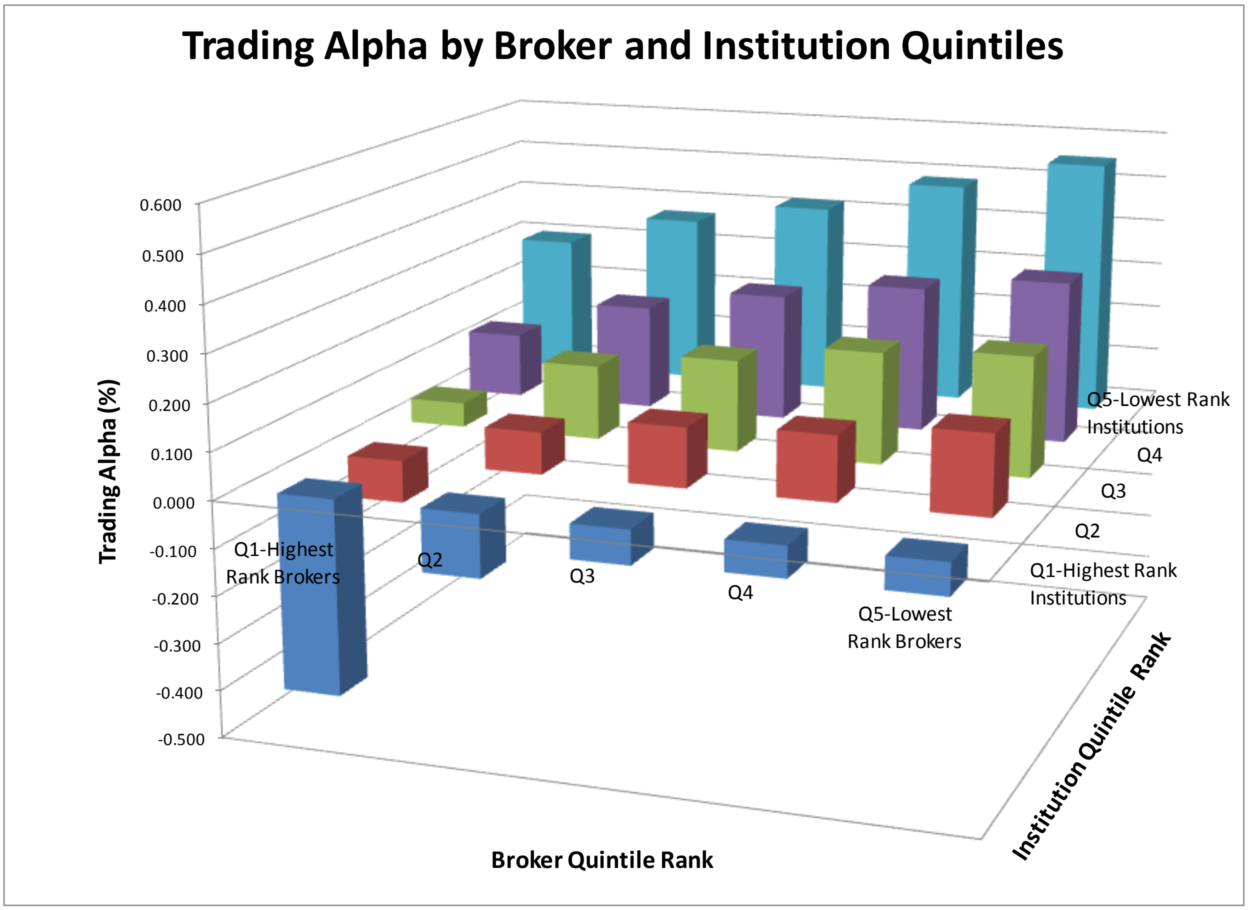


Figure 4

Drift, by Broker and Institution Quintiles, in Month M+1.

Figure 4 presents results for the post-trade drift (in percent) from the execution price until the closing price of the next day. For each month we first run monthly cross-sectional regressions separately (similar to Tables III B and IV B) using institution and broker dummy variables. Next, we use the rankings of execution shortfall associated with each broker and institution in each month and assign each broker- institution combination into one of 25 categories. Then for each month, we estimate post-trade drift for all executions in the 25 broker- institution categories, and compute an equal-weighted average for each category. We exclude institutions or brokers from a month if they have fewer than 100 ticket orders.

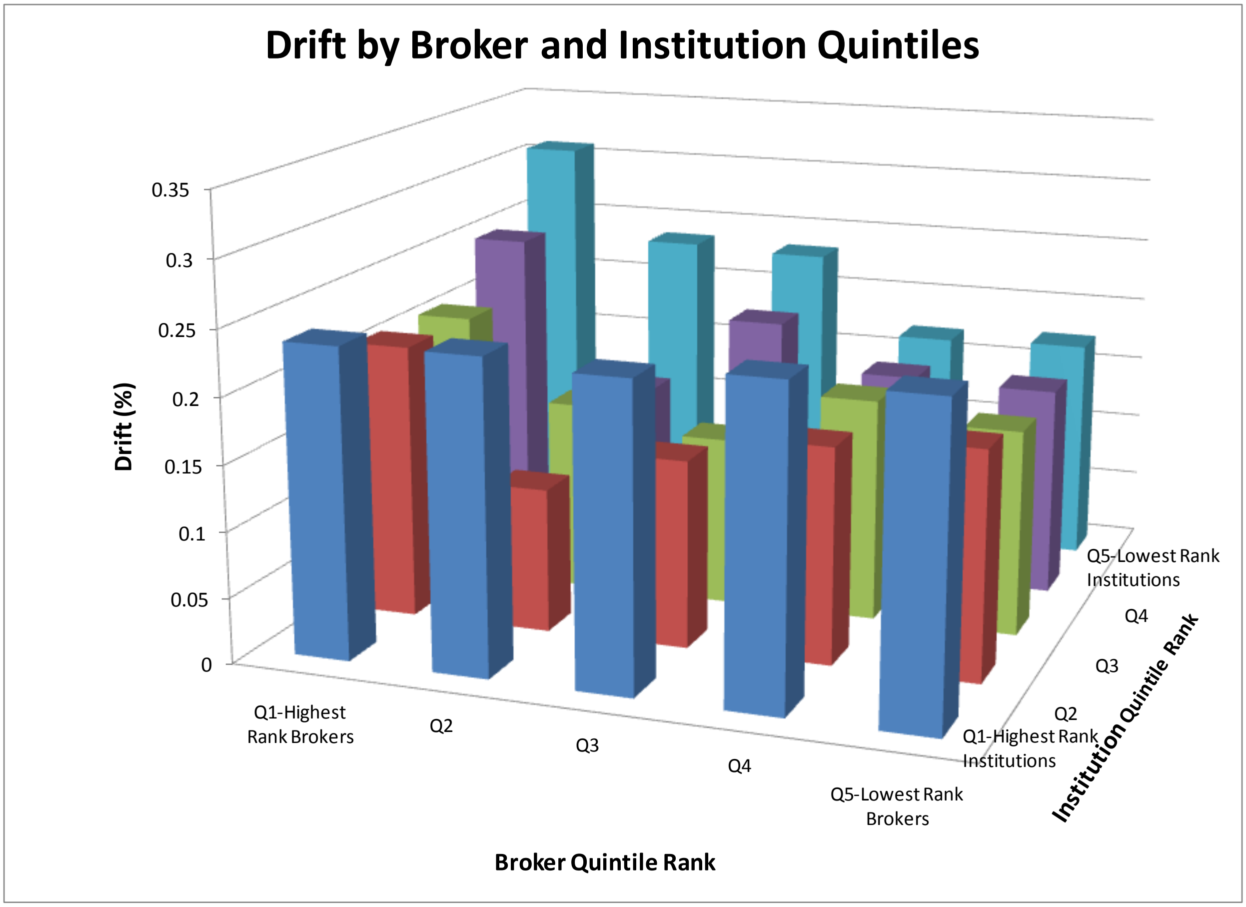


Figure 5

Commissions, by Broker and Institution Quintiles

Figure 5 presents results for average Commissions, by broker and institution quintiles, during portfolio formation month *M*. We use the execution shortfall rankings associated with each broker and institution in each month and assign each broker-institution combination into one of 25 categories. Commissions are calculated for each broker-institution portfolio by taking the equally weighted average commission (in percent) across all trades for the broker-institution combination in the month.

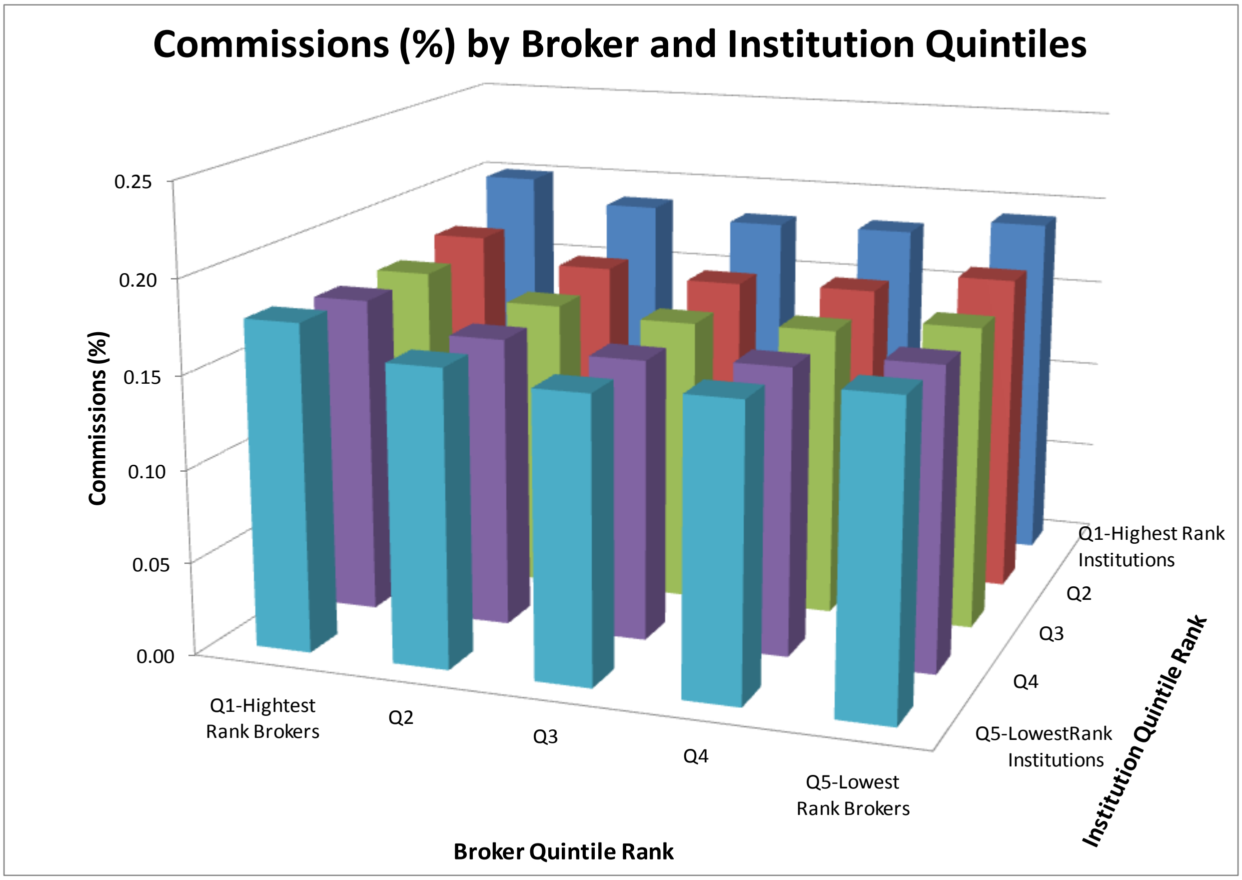


Table I
Descriptive Statistics

This table reports the descriptive statistics for our sample of institutional trades from ANcerno Ltd. for the period from January 1, 1999 to December 31, 2005. We use a ticket as our level of analysis. A ticket could be executed through multiple trades. We further restrict the sample to tickets that are executed by clients with at least 100 tickets during a particular month, as well as to tickets executed on NYSE/NASDAQ stocks. We present the results for the full sample, as well as by disaggregating the sample based on year, order direction, and firm size quintiles. Firm size quintiles are based on the stocks in our sample. Execution shortfall is measured for buy tickets as the execution price minus the market price at the time of ticket placement divided by the market price at ticket placement (for sell tickets we multiply by -1), and is reported as a percentage. Commissions are reported in dollars per share. We report the volume weighted averages for execution shortfall and commissions.

	Number of Brokers	Number of Institutions	Number of Stocks	Number of tickets	Ticket Size	Ticket Size/Average daily volume (30 days)	Number of executions per ticket	Execution Shortfall	Commissions ($/share)
Panel A: Full sample									
	1137	664	7,589	34,885,972	17,366	2.4%	1.51	0.26	0.028
Panel B: By year									
1999	670	323	5,671	3,340,323	24,088	4.8%	1.31	0.35	0.017
2000	654	321	5,442	4,449,647	23,290	3.6%	1.27	0.34	0.016
2001	686	335	4,673	5,173,781	22,583	2.7%	1.28	0.37	0.018
2002	711	358	4,365	5,725,588	15,901	2.1%	1.51	0.16	0.041
2003	681	319	4,286	5,375,277	13,666	1.8%	1.59	0.20	0.045
2004	623	307	4,358	5,548,414	12,889	1.6%	1.49	0.17	0.040
2005	633	286	4,237	5,272,942	13,067	1.7%	1.99	0.17	0.031
Panel C: Order direction									
Sell				15,844,002	19,468	2.6%	1.55	0.39	0.028
Buy				19,041,970	15,618	2.3%	1.48	0.13	0.029
Panel D: Firm size (quintiles)									
Small				58,377	8,932	33.8%	1.21	1.03	0.016
2				401,147	9,213	23.3%	1.30	0.56	0.022
3				1,961,381	8,400	8.9%	1.37	0.40	0.026
4				6,352,644	9,129	3.8%	1.37	0.27	0.029
Large				26,112,423	20,188	1.2%	1.56	0.26	0.028

Table II
Performance of Institutional Trading Desks

This table examines the performance persistence of institutional trading desks. The trades in the sample are executed by 664 institutions during the time period from January 1, 1999 to December 31, 2005. Only institutions with 100 or more tickets in a month are included in the analysis. Execution shortfall is measured for buy tickets as the execution price minus the market price at the time of ticket placement divided by the market price at ticket placement (for sell tickets we multiply by -1). We calculate the average execution shortfall across the ticket for each institution each month. At the end of the each month, we form institutions into quintile portfolios based on execution cost for the month. We report the average (equal-weighted) execution shortfall for these quintiles in the portfolio formation month and the next four months. Execution shortfall is presented as a percentage. We also include the percentage of institutions that end up in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). All numbers are in percent. Numbers in parentheses are *t*-statistics.

		Months				
Current Quarter Performance Quintiles		Portfolio Formation month	M+1	M+2	M+3	M+4
Q1	*Exec. Shortfall (%)*	-0.408	-0.072	-0.061	-0.056	-0.043
	Retention %	100.00	46.15	44.88	44.50	43.25
	Percentile	10.62	31.91	32.49	32.71	33.12
Q2	*Exec. Shortfall (%)*	0.033	0.146	0.149	0.153	0.155
	Retention %	100.00	28.91	27.27	27.49	26.99
	Percentile	30.55	42.52	43.22	43.53	43.60
Q3	*Exec. Shortfall (%)*	0.254	0.266	0.271	0.263	0.264
	Retention %	100.00	25.96	28.64	27.34	26.83
	Percentile	50.55	50.90	50.98	50.70	51.04
Q4	*Exec. Shortfall (%)*	0.486	0.383	0.376	0.373	0.365
	Retention %	100.00	28.43	28.01	28.34	26.11
	Percentile	70.51	58.36	57.95	57.61	57.21
Q5	*Exec. Shortfall (%)*	0.979	0.615	0.599	0.590	0.583
	Retention %	100.00	45.29	44.04	44.12	42.58
	Percentile	90.43	68.89	67.88	67.73	67.27
Q5 – Q1 (*Exec. Shortfall*)		**1.39**	**0.69**	**0.66**	**0.65**	**0.63**
		(169.08)	(57.07)	(53.43)	(51.32)	(49.71)

Table III, Panel A
Institution Fixed Effect Regressions of Execution Shortfall on Economic Determinants of Trading Cost

This table reports coefficient estimates from monthly institution fixed-effects regression of execution shortfall on economic determinants of execution shortfall. The model is estimated for each of the 84 months in our sample. We present the average coefficients across 84 months and the Fama-Macbeth t-statistics and p-values associated with the coefficients. We also report the proportion of coefficients that are positive. Daily return, daily S&P return, daily volume and market values are obtained from the CRSP database. The *Buy dummy* equals 1 for buy orders and 0 for sell orders. The order direction is given in the ANcerno database. *Order imbalance* is the dollar imbalance on the day prior to the day a ticket is executed. The dollar imbalance is calculated using TAQ data, and is defined as the difference of the dollar volume of buyer initiated trades and the dollar volume of seller initiated trades, divided by the total dollar volume of buyer and seller initiated trades. Trades are assigned as buyer or seller initiated using the Lee-Ready (1991) algorithm. *Momentum* is measured using the stock's return on the day prior to the ticket execution date. The return is obtained from the daily CRSP database. All explanatory variables are demeaned each month so that each institution coefficient measures the execution shortfall for an average order for the client.

	Parameter (average)	**T-statistics (F-M)**	**P-Value (F-M)**	**Positive coefficients (%)**
Number of months	84			
Stock Volatility (Absolute value of daily return)	0.03442	20.56	*0.000*	0.98
Market Volatility (Absolute value of daily S&P 500 return)	-0.01885	-3.92	*0.000*	0.35
Buy dummy	-0.00072	-2.72	*0.008*	0.37
Order imbalance (previous trading day, $)	-0.00024	-1.62	*0.108*	0.48
*Order imbalance (previous trading day, $) * Buy dummy*	0.00015	0.54	*0.593*	0.45
Momentum (Previous day's return)	-0.01835	-7.36	*0.000*	0.11
*Momentum (Previous day's return) * Buy dummy*	0.03367	7.69	*0.000*	0.87
Log (Average previous 30 day daily volume)	-0.00023	-8.20	*0.000*	0.23
Log Market value (as of the beginning of month)	0.00009	3.28	*0.002*	0.68
NYSE stock dummy (only NYSE and NASDAQ stocks included)	-0.00042	-8.04	*0.000*	0.14
1/Price	0.00585	8.49	*0.000*	0.86
Ticket Size/Average previous 30 day daily volume	0.00033	3.85	*0.000*	0.69
Adjusted R Square	0.0299			

Table III, Panel B
Persistence in Monthly Institution Trading Alpha

This table examines the persistence of monthly institutional Trading Alpha. The trades in the sample are placed by 664 different institutions during the time period from January 1, 1999 to December 31, 2005. Trading Alpha is estimated for each institution in each month using the cross-sectional regression presented in Panel A. All independent variables are de-meaned and our regression includes dummy variables for each institution. The coefficient estimate on institution dummy variables is the institution's Trading Alpha. Each month we divide all institutions into five quintiles based on their Trading Alpha estimates. We then report the average (equal-weighted) Trading Alpha for these quintiles for the portfolio formation months and the next four months. Trading Alpha is presented as a percentage. We also include the percentage of institutions that end up in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). We exclude an institution from a month if it has fewer than 100 ticket orders. All returns are in percent. Numbers in parentheses are *t*-statistics.

	Months				
Current Quarter Performance Quintiles	Portfolio Formation month	M+1	M+2	M+3	M+4
Q1 *Trading Alpha (%)*	-0.311	-0.146	-0.133	-0.130	-0.122
Retention %	100.00	55.97	54.23	53.10	52.08
Percentile	10.62	25.87	27.22	27.68	28.18
Q2 *Trading Alpha (%)*	0.022	0.084	0.078	0.080	0.085
Retention %	100.00	32.13	32.96	31.25	29.91
Percentile	30.54	41.32	41.32	41.95	42.34
Q3 *Trading Alpha (%)*	0.174	0.170	0.176	0.173	0.168
Retention %	100.00	32.63	32.69	31.65	29.59
Percentile	50.55	50.74	51.17	51.43	51.40
Q4 *Trading Alpha (%)*	0.321	0.271	0.261	0.253	0.246
Retention %	100.00	33.55	31.44	30.10	30.33
Percentile	70.52	60.78	60.10	59.33	58.81
Q5 *Trading Alpha (%)*	0.653	0.471	0.448	0.442	0.436
Retention %	100.00	53.97	51.61	50.75	50.90
Percentile	90.39	73.89	72.61	71.98	71.61
Q5 – Q1 (*Trading Alpha*)	**0.96**	**0.62**	**0.58**	**0.57**	**0.56**
	(141.48)	(69.35)	(63.42)	(61.24)	(58.90)

Table IV, Panel A
Broker Fixed Effect Regressions of Execution Shortfall on Economic Determinants of Trading Cost

This table reports coefficient estimates from monthly broker fixed-effects regression of execution shortfall on economic determinants of execution shortfall. The model is estimated for each of the 84 months in our sample. We present the average coefficients across 84 months, and the Fama-Macbeth t-statistics and p-values associated with the coefficients. We also report the proportion of coefficients that are positive. Daily return, daily S&P return, daily volume and market values are obtained from the CRSP database. The *Buy dummy* equals 1 for buy orders and 0 for sell orders. The order direction is given in the ANcerno database. *Order imbalance* is the dollar imbalance on the day prior to the day a ticket is executed. The dollar imbalance is calculated using TAQ data, and is defined as the difference of the dollar volume of buyer initiated trades and the dollar volume of seller initiated trades, divided by the total dollar volume of buyer and seller initiated trades. Trades are assigned as buyer or seller initiated using the Lee-Ready (1991) algorithm. *Momentum* is measured using the stock's return on the day prior to the ticket execution date. The return is obtained from the daily CRSP database. All explanatory variables are demeaned each month so that each broker coefficient measures the execution shortfall for an average order for the broker.

	Parameter (average)	**T-statistics (F-M)**	**P-Value (F-M)**	**Positive coefficients (%)**
Number of months	84			
Stock Volatility (Absolute value of daily return)	0.03603	21.73	*0.000*	0.98
Market Volatility (Abs. value of daily S&P 500 ret)	-0.01952	-4.01	*0.000*	0.33
Buy dummy	-0.00076	-2.80	*0.006*	0.38
Order imbalance (previous trading day, $)	-0.00025	-1.69	*0.094*	0.50
*Order imb (previous trading day, $) * Buy dum*	0.00026	0.92	*0.358*	0.46
Momentum (Previous day's return)	-0.02010	-7.88	*0.000*	0.10
*Momentum (Previous day's return) * Buy dummy*	0.03714	8.21	*0.000*	0.88
Log (Average previous 30 day daily volume)	-0.00027	-9.65	*0.000*	0.18
Log Market value (as of the beginning of month)	0.00017	6.74	*0.000*	0.75
NYSE stock dummy (only NYSE and NASDAQ stocks included)	-0.00070	-10.09	*0.000*	0.06
1/Price	0.00527	8.05	*0.000*	0.83
Ticket Size/Average previous 30 day daily volume	0.00048	4.89	*0.000*	0.75
Adjusted R Square	0.0249			

Table IV, Panel B
Persistence of Monthly Broker Trading Alpha

Table 4, Panel B examines the persistence of monthly broker Trading Alpha. The sample includes all trades by 431 different brokerage firms that executed at least 100 trades in a month during the time period from January 1, 1999 to December 31, 2005. Trading Alpha is estimated for each brokerage firm in each month using the broker fixed effects regression presented in Panel A. All independent variables are de-meaned and our regression includes dummy variables for each brokerage firm. The coefficient estimate on brokerage firm dummy variables is the brokerage firm's Trading Alpha. Each month we divide all brokerage firms into five quintiles based on their Trading Alpha estimates. We then report the average (equal-weighted) Trading Alpha for these quintiles for the portfolio formation months and the next four months. Trading Alpha is presented as a percentage. We also include the percentage of brokerage firms that end up in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile brokerage firms (*Percentile*). All returns are in percent. Numbers in parentheses are *t*-statistics.

		Months			
Current Quarter Performance Quintiles	Portfolio Formation month	M+1	M+2	M+3	M+4
Q1 *Trading Alpha (%)*	-0.314	-0.007	0.004	0.007	0.003
Retention %	100.00	42.93	41.26	39.83	41.46
Percentile	10.76	37.26	37.86	38.91	38.20
Q2 *Trading Alpha (%)*	0.069	0.150	0.147	0.147	0.143
Retention %	100.00	27.98	26.93	26.27	26.97
Percentile	30.56	46.79	47.12	46.90	47.12
Q3 *Trading Alpha (%)*	0.193	0.208	0.184	0.195	0.188
Retention %	100.00	28.63	28.75	26.83	27.91
Percentile	50.56	53.01	51.12	52.25	52.47
Q4 *Trading Alpha (%)*	0.308	0.229	0.226	0.207	0.205
Retention %	100.00	27.59	27.77	26.94	26.69
Percentile	70.57	56.10	56.12	55.05	54.96
Q5 *Trading Alpha (%)*	0.620	0.277	0.279	0.257	0.255
Retention %	100.00	34.68	35.17	33.17	32.87
Percentile	90.33	59.42	60.16	58.99	59.08
Q5 – Q1 (*Trading Alpha*)	**0.93**	**0.28**	**0.28**	**0.25**	**0.25**
	(84.90)	(20.61)	(19.53)	(17.99)	(18.29)

Table V, Panel A
Persistence in Institutional Trading Alpha within Broker Groups

This table presents results for the persistence in institutional trading alpha, controlling for the execution quality of brokerage firms. For each month we first run monthly cross-sectional regressions separately (similar to Tables III B and IV B) using institution and broker dummy variables. Next, we use the rankings associated with each broker and institution in each month and assign each broker-institution combination into one of 25 categories. Then for each month, we estimate regressions using the execution shortfall as the dependent variable, and the control variables described earlier as well as the 25 broker-institution combination dummies as the independent variables (this specification excludes broker and client dummy variables). We use each month's broker-institution combination ranking to estimate similar regression for the next 4 months. Our methodology produces 25 coefficient estimates (that represent all possible institution-broker rank combinations) for the formation month (*M*) and the subsequent four months. For each period and brokerage firm quintile, we hold the broker ranking constant and report the difference between the highest institutional quintile (quintile=1) and lowest institutional quintile (quintile=5). We exclude institutions or brokers from a month if they have fewer than 100 ticket orders. Trading Alpha is presented as a percentage. Numbers in parentheses are t-statistics. Quintile differences are presented in bold font.

		Difference in trading alpha between highest and lowest institutional quintile				
Broker quintile rankings		Portfolio Form. month	*M+1*	*M+2*	*M+3*	*M+4*
q1 (best)	Q1	-0.689	-0.416	-0.396	-0.370	-0.352
	Q5	0.279	0.300	0.267	0.250	0.266
	Q5-Q1	**0.967**	**0.715**	**0.663**	**0.619**	**0.618**
		(33.62)	(24.11)	(21.36)	(17.86)	(18.17)
q2	Q1	-0.350	-0.133	-0.107	-0.091	-0.103
	Q5	0.446	0.369	0.365	0.358	0.353
	Q5-Q1	**0.796**	**0.502**	**0.4471**	**0.449**	**0.456**
		(36.96)	(20.59)	(27.50)	(19.05)	(20.70)
q3	Q1	-0.232	-0.073	-0.089	-0.048	-0.034
	Q5	0.553	0.417	0.404	0.418	0.392
	Q5-Q1	**0.784**	**0.489**	**0.492**	**0.466**	**0.426**
		(30.68)	(21.80)	(19.62)	(19.36)	(18.47)
q4	Q1	-0.138	-0.066	-0.044	-0.044	-0.032
	Q5	0.661	0.486	0.454	0.448	0.457
	Q5-Q1	**0.799**	**0.551**	**0.498**	**0.492**	**0.489**
		(30.13)	(22.26)	(22.02)	(18.45)	(17.94)
q5 (worst)	Q1	0.097	-0.067	-0.089	-0.044	-0.009
	Q5	0.883	0.551	0.578	0.547	0.539
	Q5-Q1	**0.785**	**0.618**	**0.667**	**0.591**	**0.547**
		(18.24)	(17.32)	(15.29)	(17.38)	(16.02)

Table V, Panel B
Persistence in Broker Trading Alpha within Institutional Groups

This table presents results for the persistence in broker trading alpha, controlling for the execution quality of institutions. For each month we first run monthly cross-sectional regressions separately (similar to Tables III B and IV B) using institution and broker dummy variables. Next, we use the rankings associated with each broker and institution in each month and assign each broker-institution combination into one of 25 categories. Then for each month, we estimate regressions using the execution shortfall as the dependent variable, and the control variables described earlier as well as the 25 broker-institution combination dummies as the independent variables (this specification excludes broker and institution dummy variables). We use each month's broker-institution combination ranking to estimate similar regression for the next 4 months. Our methodology produces 25 coefficient estimates (that represent all possible institution-broker rank combinations) for the formation month (*M*) and the subsequent four months. For each period and institution quintile, we hold the institution ranking constant and report the difference between the highest broker quintile (quintile=1) and lowest broker quintile (quintile=5). We exclude institutions or brokers from a month if they have fewer than 100 ticket orders. Trading Alpha is presented as a percentage. Numbers in parentheses are t-statistics.

		Difference in trading alpha between highest and lowest broker quintile				
Institution quintile rankings		Portfolio Form. month	*M+1*	*M+2*	*M+3*	*M+4*
q1 (best)	Q1	-0.689	-0.416	-0.396	-0.370	-0.352
	Q5	0.097	-0.067	-0.089	-0.044	-0.009
	Q5-Q1	**0.785**	**0.348**	**0.306**	**0.326**	**0.343**
		(22.66)	(11.64)	(8.89)	(9.80)	(11.27)
q2	Q1	-0.288	-0.090	-0.094	-0.067	-0.068
	Q5	0.331	0.170	0.152	0.146	0.141
	Q5-Q1	**0.619**	**0.261**	**0.246**	**0.212**	**0.209**
		(21.52)	(11.32)	(11.19)	(8.84)	(8.09)
q3	Q1	-0.080	0.052	0.046	0.066	0.054
	Q5	0.430	0.255	0.256	0.245	0.253
	Q5-Q1	**0.510**	**0.202**	**0.209**	**0.179**	**0.199**
		(19.42)	(10.02)	(9.97)	(8.15)	(9.39)
q4	Q1	0.029	0.139	0.119	0.115	0.098
	Q5	0.585	0.347	0.365	0.340	0.318
	Q5-Q1	**0.556**	**0.208**	**0.246**	**0.225**	**0.220**
		(20.16)	(9.29)	(9.59)	(8.77)	(9.28)
q5 (worst)	Q1	0.279	0.300	0.267	0.250	0.266
	Q5	0.882	0.551	0.578	0.547	0.539
	Q5-Q1	**0.603**	**0.251**	**0.310**	**0.296**	**0.272**
		(16.82)	(9.17)	(8.49)	(9.72)	(8.06)

Table VI
Performance Attribution

This table decomposes the trading desk performance difference between [top institution, top broker] and [bottom institution, bottom broker] fractiles (as observed in Figure III) into two components – broker selection and institutional skill. The table reports the trading alpha and the broker market share for institutions in month *M+1*. Column (1) presents a hypothetical "most skilled" Quintile 1 institution with perfect foresight that routes 100 percent of its trades to the best brokers. Similarly, column (4) presents a hypothetical "least skilled" Quintile 5 institution with poor foresight that routes 100 percent of its trades to the worst brokers. The trading alpha difference between the hypothetical "most skilled" and "least skilled" institution is (0.551% - (-0.416%) =) 0.97%. Columns (2) and (3) present the trading alpha and broker market share for the average Quintile 1 and Quintile 5 institutions, respectively, across all broker quintiles based on data during the sample period. The trading alpha by broker quintiles in columns (1) and (2) (and also, columns (3) and (4)) are identical, reflecting that institutions within a quintile are equally skilled and receive similar executions from a broker.

	(1) Most Skilled Institution		(2) Quintile 1 Institution		(3) Quintile 5 Institution		(4) Least Skilled Institution	
	Broker Mkt share	Trading Alpha (%)	Broker Mkt share	Trading Alpha (%)	Broker Mkt share	Trading Alpha (%)	Broker Mkt share	Trading Alpha (%)
Q1 (Best Broker)	100%	-0.416	13.6%	-0.416	8.1%	0.300	0%	0.300
Quintile 2	0%	-0.133	30.6%	-0.133	25.4%	0.369	0%	0.369
Quintile 3	0%	-0.073	32.3%	-0.073	31.2%	0.417	0%	0.417
Quintile 4	0%	-0.066	18.5%	-0.066	23.7%	0.486	0%	0.486
Q5 (Worst Broker)	0%	-0.067	5.0%	-0.067	11.7%	0.551	100%	0.551
Trading Alpha (%)	-0.416		-0.136		0.427		0.551	

Table VII
Broker and Institution Cross-Sectional Regressions

This table presents cross-sectional regressions where the monthly estimated Institution (Broker) trading alpha is the dependent variable. *Herfindahl-I*, for institutions, captures institutional concentration of trading volume among the brokers they use. *Herfindahl-B* for brokers captures the concentration of a broker's trading by FF industry groups. *Commissions* is the average commission (in percent) of all ticket orders for the Institution (Broker) in the month. *Ticket Size* is the average dollar value of all ticket orders for the Institution (Broker) in the month. *Executions per ticket* is the average number of executions for each ticket during the month. *Number of clients* is the total number of institutional clients that traded with a broker in a month, while *number of brokers* is the total number of brokers that traded with an institution in a month. *Bulge Broker* is a set of 7 highly capitalized brokers constructed from external capital variables obtain from FINRA, while *Client Size quintiles* are based on the total dollar value of monthly trading for a client. We present the average coefficients across 84 months and the Fama-Macbeth t-statistics and p-values associated with the coefficients.

	Institution Trading Alpha			**Broker Trading Alpha**		
	Parameter (average)	**T-statistics (F-M)**	**P-Value (F-M)**	**Parameter (average)**	**T-statistics (F-M)**	**P-Value (F-M)**
Intercept	0.3286	14.11	*0.000*	0.1971	8.63	*0.000*
Herfindahl-I	-0.1522	-6.38	*0.000*			
Herfindahl-B				-0.1055	-2.22	*0.029*
Commissions	-1.0417	-11.88	*0.000*	-0.4053	-4.67	*0.000*
Ticket Size ($)	0.0255	6.76	*0.000*	0.0377	8.36	*0.000*
Executions per Ticket				-0.0057	-2.21	*0.030*
Number of Clients				0.0003	6.77	*0.000*
Number of Brokers	0.0001	0.83	*0.408*			
Bulge Broker				-0.0298	-3.86	*0.000*
Largest Client Quintile	-0.0583	-6.20	*0.000*			
Quintile 2	-0.0524	-6.33	*0.000*			
Quintile 3	0.0085	0.97	*0.334*			
Quintile 4	-0.0078	-0.95	*0.342*			
Number of Observations	20,551			12,766		
Adjusted R Square	0.0335			0.0274		