Performance of Institutional Trading Desks: An Analysis of Persistence in Trading Costs

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Using a proprietary dataset of institutional investors' equity transactions, we document that institutional trading desks can sustain relative performance over adjacent periods. We find that trading-desk skill is positively correlated with the performance of the institution's traded portfolio, suggesting that institutions that invest resources in developing execution abilities also invest in generating superior investment ideas. Although some brokers can deliver better executions consistently over time, our analysis suggests that trading-desk skill is not limited to a selection of better brokers. We conclude that the trade implementation process is economically important and can contribute to relative portfolio performance. (*JEL* G12, G23, G24)

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Trading costs for institutional investors can be economically large.[1] One approach that can be used to measure 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 security positions were acquired at 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 a paper portfolio based on the Value Line ranking system outperformed the market by 20% per year, and the real Value Line fund, which implemented the trades recommended in the newsletter, outperformed the market by only 2.5% per year, emphasizing that the quality of implementation is at least as important as the investment idea itself.

This 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 an important category of financial intermediaries, namely trading desks, which are responsible for trillions of dollars in executions each year. In this article, we establish the importance of trading desks for managed portfolio performance by documenting economically substantial heterogeneity and, more importantly, persistence in trading costs across institutional investors.

Since Jensen's (1968) publication, many of the tests in the performance measurement literature examine performance persistence: whether past portfolio performance is informative about future portfolio performance. Several recent studies on mutual funds (see, e.g., Kacperczyk and Seru 2007; Bollen and Busse 2005; Busse and Irvine 2006) find 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 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 identity of the fund be a source of relative performance? Is the buy-side trading desk part of the explanation? Trading costs have the ability to erode or eliminate the value added by portfolio managers. Managers rely on buy-side trading desks in order to implement their investment ideas. A trading desk can add value to an institution's portfolio by supplying expertise in locating

[1] For example, using institutional data provided by the Plexus Group, Chiyachantana, Jain, Jiang, and Wood (2004) report average one-way trading costs of forty-one basis points for 1997–1998 and thirty-one 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 et al. (2009).

counterparties and formulating trading strategies. Therefore, it is natural to ask whether the execution process contributes to differential institutional performance. Unfortunately, the information necessary to estimate institutional trading costs is difficult to obtain from publicly available sources. For example, the NYSE's Trade and Quote (TAQ) database does not identify the institution associated with a trade, provide information about whether a trade was a buy or a sell, or provide information about whether a trade represented all or part of an institutional investor's larger package of trades.

We examine a proprietary database of institutional investor equity transactions compiled by Ancerno Ltd. (formerly the Abel/Noser Corporation). The data contain approximately forty-eight million tickets that are initiated by 750 institutional investors and facilitated by 1,216 brokerage firms over the ten-year period of 1999–2008. The Ancerno database is distinctive in that it contains a detailed history of trading activity by each institution. Furthermore, the dataset provides information on tickets sent by an institution to a broker; each ticket typically results in more than one execution. The data for each ticket include stock identifiers that help in obtaining relevant data from other sources and, more importantly for this study, codes that identify the institution and the broker. The detailed transaction-level Ancerno dataset seems particularly well suited for studying whether trading desks can sustain relative performance and contribute to fund performance persistence.

Our article focuses on a literature that examines heterogeneity in transaction costs for specific intermediaries. Linnainmaa (2007) uses Finnish data to argue for differences in execution costs across retail and institutional broker types. Conrad, Johnson, and Wahal (2001) document the relation between soft-dollar arrangements and institutional trading costs. 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 article complements this body of literature, using more extensive trading data that allow us to integrate both institutional execution and broker execution into a single framework. To the best of our knowledge, this is the first study to directly examine persistence in trading performance 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 that is observed when the trading desk sends the ticket to the broker. It reflects the bid-ask spread, the market impact, and the drift in price, while executing the order. We sort trading desks on the basis of execution shortfall during the portfolio formation month and create quintile portfolios. The difference in (one-way) trading costs between the low- and high-cost trading-desk quintiles in the portfolio formation month is 131 bp. Typically, around sixty basis points of these cost differences persist into future months. Remarkably, the low-cost trading desks exhibit a persistent pattern of *negative* execution shortfall. Results are similar when we control for the economic determinants of trading costs, such as ticket attributes, stock characteristics, and market conditions, or when the performance is based on “stitched” ticket orders, which involves aggregating an institution’s related tickets over adjacent trading days. Our findings suggest that trading desks can sustain relative outperformance over time and that the best desks can contribute to portfolio performance through their trading strategies.

Building on this idea, we investigate the relationship between an institution’s trading costs and the holding-period returns of securities that the institution buys and sells, which we term *portfolio performance*. Institutional investors with short-lived private information may be willing to incur higher trading costs in order to exploit their temporary information advantage. If high-cost institutions are trading on valuable short-lived private information, the abnormal *portfolio performance* of high-cost institutions should exceed that of low-cost institutions. Instead, we find that high-cost institutions have lower abnormal portfolio performance. The results suggest that when institutions invest resources in developing execution abilities, they also invest in the generation of superior investment ideas.

One prominent decision made by the buy-side trading desk is broker selection. We examine whether some brokers can consistently deliver better executions and find significant heterogeneity in execution quality across brokers. Importantly, brokers ranked as best (low-cost) performers during the portfolio formation month continue to deliver the lowest trading cost in subsequent months. In fact, the best brokers can consistently execute trades with almost no price impact. Our findings suggest that broker selection on the basis of past performance should be an important dimension of a portfolio manager’s best execution obligations.

We also exploit the detailed ticket-level data on institutions and brokers in order to estimate the broker’s contribution to trading-desk performance. We find that trading desks benefit when they select better brokers. In terms of economic significance, we estimate that, after controlling for the quality of the institutional trading desk that routes the order, the trading-cost difference between a low-cost Q1 broker and a high-cost Q5 broker is sixteen basis points. However, institutions can do considerably better or worse than the average performance of the brokers they employ, and we find that trading-desk skill is not limited to the selection of better brokers. After controlling for broker selection, we estimate that the low-cost trading desks outperform the high-cost trading desks by approximately forty basis points.

We find that order-routing decisions by institutions are highly persistent. Moreover, poorly performing brokers only slowly lose market share, which suggests that institutions employ brokers for reasons other than superior trade execution. Goldstein et al. (2009) illustrate how some brokers are execution-only, while other full-service brokers are selected in order to obtain ancillary benefits, such as research and profitable IPO allocations. We classify all brokers into either execution-only or full-service categories and separately examine trading-desk persistence for tickets routed to each broker type. We find significant persistence for both types of brokers. However, the persistent differences are larger for full-service trades, which can be attributed to the weak performance of high-cost institutions that use full-service brokers. This weak performance result is consistent with Conrad, Johnson, and Wahal (2001), who report that some institutions receive poor executions, despite paying relatively high commissions on certain trades.

An implication for institutions is that the benefits of the bundled services provided by high-cost brokers need to exceed not only explicit commission costs but also the larger implicit trading costs that this study documents for high-cost brokers. Furthermore, the low portfolio performance of high-cost institutions does not support the contention that these institutions receive valuable research services from high-cost brokers that contribute to relative fund performance. We also find that institutions care more about past broker performance when using ECNs, discount brokers, or other execution-only brokers than when using full-service brokers. This suggests that bundling execution and services can inhibit price competition among brokers.

This article is organized as follows: In Section 1, we describe the institutional trading process and review the literature on measuring institutional trading costs. Execution cost measures and the sample selection are described in Section 2. In Section 3, we report the results on trading-cost persistence of institutional trading desks. In Section 4, we relate trading-cost persistence to portfolio performance. In Section 5, we consider possible explanations for trading cost-persistence. Section 6 discusses the implications of our findings for regulators and market participants, and Section 7 concludes.

1. Background

1.1 The institutional trading process

A typical order originates at a buy-side institution with a portfolio manager, who hands off the order with instructions to the buy-side trading desk. The trading desk makes a set of choices to meet its 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.

Trading desks supply expertise in measuring execution quality, developing broker selection guidelines, 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 who trades on longer-term information, can both 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.[2] The trading problem is especially difficult for orders that are large relative to the daily trading volume for a security. Some large traders 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 increasingly electronic marketplace, trading desks specialize in building trading algorithms to detect pools of hidden liquidity (see Bessembinder, Panayides, and Venkataraman 2009) and quickly respond to market conditions.

1.2 Measuring execution costs of institutional trades

Prior research has recognized that trading costs can be a drag on managed portfolio performance (see, e.g., Carhart 1997). Since transaction data for institutional traders are not publicly available, previous work that relates institutional performance and trading costs has predominantly relied on quarterly ownership data. A commonly used measure for trading costs is the fund turnover, which is 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/or incur similar costs in executing their trades.

Another measure, which was proposed by Grinblatt and Titman (1989) and recently implemented 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, Sialm, and Zheng (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.

[2] Empirical 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. Since there is a lack of data, we follow Keim and Madhavan (1997) and do not assign a cost to any portion of the desired order that is not executed. However, we realize that this assumption of 100% fill rates may be more valid at the institution level than at the broker level. We discuss this issue in greater detail and present a robustness analysis in Section 5.4.

Other studies, such as Wermers (2000), estimate the trading cost of mutual funds using the regression coefficients from Keim and Madhavan (1997), who examine a sample of institutional trades between 1991 and 1993. Edelen, Evans, and Kadlec (2007) propose a new measure that combines changes in quarterly ownership data with trading costs estimated for each stock from NYSE TAQ data. However, as acknowledged by these studies, these approaches do not capture the heterogeneity in institutional trading costs that can be attributed to the skill of the trading desk.

Our study is distinguished from earlier work because we examine persistence in institutional trading performance and estimate, with greater precision, the trading costs that are associated with *each* institution. By analyzing detailed institutional trade-by-trade data, we capture the heterogeneity in trading efficiency or skill across trading desks. Moreover, the dataset contains the complete history of trades executed by each institution. Thus, we observe the institutional activity (purchases and sales) within a quarter, which cannot be observed from changes in quarterly snapshots of fund holdings.[3]

Prior research that uses the Plexus database has made important contributions to our understanding of institutional trading costs.[4] However, Plexus data cannot be used to establish trading-cost persistence because Plexus changes the anonymous institutional identifiers every month and thus makes it impossible to track the performance of an institution over time. In contrast, Ancerno retains an institution's unique identifier 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 later discussed, we overcome this data deficiency by controlling for the style characteristics of the stocks that each institution trades.

2. Execution Shortfall Measure and Descriptive Statistics of the Sample

2.1 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 price follows prior literature and relies on the implementation shortfall approach described in Perold (1988).[5] We define execution shortfall for a ticket as follows:

[3] Elton et al. (2010) and Puckett and Yan (2011) estimate that intraquarter round-trip trades, which cannot be observed using changes in quarterly portfolio holdings, account for approximately 20% of a fund's total trading volume.

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

[5] Some studies (see Berkowitz, Logue, and Noser 1988; Hu 2009) have argued that the execution price should be compared with the volume-weighted average price (VWAP), a popular benchmark among practitioners.

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

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 one for a buy ticket and minus one for a sell ticket.

2.2 Sample descriptive statistics

We obtain data on institutional trades for the period from January 1, 1999, to December 31, 2008, from Ancerno Ltd. Ancerno is a widely recognized consulting firm that works with institutional investors to monitor execution costs. Ancerno's clients include pension plan sponsors, such as CALPERS, the Commonwealth of Virginia, and the YMCA retirement fund, as well as money managers, such as Massachusetts Financial Services, Putman Investments, Lazard Asset Management, and Fidelity. Previous academic studies that use Ancerno's data include Goldstein et al. (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2010), and Puckett and Yan (2011).

Summary statistics for Ancerno's trade data are presented in Table 1. The sample contains a total of 750 institutions that are responsible for approximately forty-eight million tickets, which lead to 104 million trade executions.[6] Over the ten-year sample period, the average length of time that an institution appears in the database is forty-six months and more than 60% of the institutions in the database are present for at least twenty-four months. For each execution, the database reports identity codes for the institution and the broker involved in each trade, a reference file for brokers that permits broker identification, 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. As per Ancerno's officials, the database captures the complete history of all transactions of the institutions. The institution's identity is restricted in order to protect the privacy of Ancerno's clients, but the unique client code facilitates identification of an institution both in the cross-section and through time.[7] We provide a more detailed description of the Ancerno database, the variables contained in the database, and the mechanism for data delivery from institutions to Ancerno in the Appendix.

Madhavan (2002) and Sofianos (2005) present a detailed discussion of the VWAP strategies and the limitations of the VWAP benchmark.

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

[7] For the sample period preceding the explosion in trading activity from algorithmic trading desks (1999–2005), we estimate that Ancerno institutional clients are responsible for approximately 8% of total CRSP daily dollar volume. We include only stocks with sharecode equal to ten or eleven in our calculation. Further, we divide the 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.

Table 1
Descriptive statistics

	No. of Brokers	No. of Institutions	No. of Stocks	No. of tickets	Ticket Size	Ticket Size/Avg. daily vol. (%)	No. of executions/ ticket	Execution Shortfall	Commissions ($/share)
Panel A: Full sample									
	1216	750	8,275	48,775,663	15,790	2.1	2.13	0.25	0.028
Panel B: By year									
1999	667	323	5,671	3,340,323	24,088	4.8	1.31	0.35	0.017
2000	651	321	5,442	4,449,647	23,290	3.6	1.27	0.34	0.016
2001	682	335	4,673	5,173,781	22,583	2.7	1.28	0.37	0.018
2002	708	358	4,365	5,725,588	15,901	2.1	1.51	0.16	0.041
2003	678	319	4,286	5,375,277	13,666	1.8	1.59	0.20	0.045
2004	620	307	4,358	5,548,414	12,889	1.6	1.49	0.17	0.040
2005	631	286	4,237	5,272,942	13,067	1.7	1.99	0.17	0.031
2006	597	284	4,195	4,950,685	12,139	1.4	3.49	0.16	0.027
2007	549	259	4,212	4,619,523	11,338	1.2	4.61	0.17	0.025
2008	474	223	3,919	4,319,483	12,001	1.0	2.92	0.32	0.023
Panel C: Order direction									
Sell				22,378,225	17,486	2.2	2.18	0.37	0.027
Buy				26,397,438	14,352	2.0	2.08	0.13	0.028
Panel D: Firm size (quintiles)									
Small				95,201	9,147	32.3	1.28	0.88	0.017
2				637,260	9,152	19.2	1.43	0.50	0.022
3				2,993,744	8,318	7.1	1.53	0.36	0.026
4				9,074,031	9,081	3.1	1.52	0.27	0.028
Large				35,975,427	18,239	1.0	2.34	0.24	0.028

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, 2008. The analysis is conducted by using institutional tickets, which could be executed through multiple trades. We restrict the sample to tickets, where the broker handling the ticket can be identified, the execution shortfall is less than or equal to 10%, the executed ticket volume is less than or equal to the total daily trading volume reported in CRSP, the institution responsible for the ticket has at least 100 tickets during a particular month, and the ticket is for a common stock listed on NYSE or NASDAQ and has data available in the CRSP and TAQ databases. We present descriptive statistics for the full sample, as well as by disaggregating the sample based on year, order direction, and firm-size quintiles. Firm-size quintile breakpoints are constructed by using 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.

In the Appendix, we also present two comparisons between Ancerno data and the 13F database. The first analysis compares the portfolio *holdings* for a subsample of institutional names—that were separately provided to us by Ancerno—against all institutions in the Thompson 13F database, while the second analysis compares the cumulative quarterly *trading* of all institutions in the Ancerno database to the inferred quarterly trading of all 13F institutions. The inferred trading of 13F institutions is based on changes in the quarterly holdings. The characteristics of stocks held and traded by Ancerno institutions are not significantly different from the characteristics of stocks held and traded by the average 13F institution. The subsample of Ancerno institutions appears larger than the average 13F institution in the number of unique stockholdings (608 vs. 248), total net assets ($24.5 billion vs. $4.3 billion), and dollar value of trades ($1.6 billion vs. $1.3 billion). In addition, we recognize a potential implicit selection bias in the Ancerno sample, since Ancerno's clients choose to employ the services of a transaction cost analysis expert and are probably more mindful of their best execution obligations than is the average 13F institution. For this reason, our analysis of Ancerno institutions might understate the heterogeneity and importance of trading costs for portfolio performance.

To minimize observations with errors and obtain the necessary data for our empirical analysis, we impose the following screens: 1) Require that the broker associated with each ticket can be uniquely identified; 2) delete tickets with execution shortfall greater than an absolute value of 10%; 3) delete tickets with ticket volume greater than the stock's CRSP volume on the execution date; 4) only include common stocks listed on NYSE or NASDAQ with data available in the CRSP and TAQ databases; and 5) 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. We obtain market capitalization, returns, trading volume, and the listed exchange from CRSP; and daily dollar order imbalance from TAQ.

There are several notable time-series patterns in institutional trading observed in Table 1, Panel B. The number of brokers and institutions in the database peaked in 2002 and declined toward the end of the sample period. The number of traded stocks has also declined from 5,671 in 1999 to 3,919 in 2008, while volume has been over four million tickets for all years except 1999. The average ticket size has declined from 24,088 in 1999 to 12,001 in 2008, with a significant decline that coincides with the move to decimal trading for equities in 2001. Consistent with the findings in Bessembinder (2003), who estimates spread-based measures by using TAQ data, we observe a decline in execution shortfall with decimal trading but an increase in commissions.[8] From Panel C of Table 1, we note that the execution shortfall for sell tickets

[8] Harris (1999) predicts that decimalization will lower the bid-ask spread, but can also inhibit incentives for liquidity provision and cause large traders to split orders. Consistent with Harris's argument, Jones and Lipson (2001) find that the NYSE reduction of tick size from eighths to sixteenths caused large traders to split orders into multiple trades. Sofianos (2001) remarks that the reduction in spreads that accompanied decimalization in 2001

(thirty-seven basis points) exceeds that for buy tickets (thirteen basis points), which is consistent with Chiyachantana et al. (2004). In Panel D, we report that the average ticket for *Small* quintile stocks represents a remarkable 32.3% of the stocks' daily trading volume, while the corresponding number for *Large* quintile stocks is only 1.0%. Clearly, tickets for small stocks are more difficult to execute, as they experience an average execution shortfall of eighty-eight basis points.

3. Performance of Institutional Trading Desks

3.1 Persistence in institutional execution shortfall

Table 2 presents our initial examination of trading-desk performance. For each institution, we calculate the execution shortfall for each ticket and then the volume-weighted execution shortfall across all tickets for the month. We place institutions in quintile portfolios (Q1: low-cost; Q5: high-cost) on the basis of monthly execution shortfall during the formation month (month M). Table 2 presents an equally weighted average across all institutions in each quintile.[9]

There is a large and significant difference of 131 bp between the low- and high-cost institutions in the portfolio formation month. The low-cost institutions execute trades with a negative execution shortfall of thirty-nine basis points, while high-cost institutions execute trades with an execution shortfall of ninety-two basis points. However, there are myriad 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 2, we report the average execution shortfall in future months, $M + 1$ through $M + 4$, for institutions sorted into execution-cost quintiles in month M. Our choice to examine persistence over short measurement periods (four months) follows recent studies on mutual fund performance (see, e.g., Bollen and Busse 2005; Busse and Irvine 2006), that examine fund persistence over short periods. In month $M + 1$, we note that institutions that are placed in low-cost Q1 during month M report a negative execution shortfall of seven basis points. In contrast, institutions that are placed in high-cost Q5 experience an average execution shortfall of fifty-seven basis points. We also note that the execution shortfall in month $M + 1$ monotonically increases from Q1 to Q5. The difference in month $M + 1$ performance between low- and high-cost quintiles is sixty-four basis points (t-statistic of difference $= 16.68$). To account for possible dependencies in both the cross-section and through time, we compute

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.

9 Value-weighted construction across institutions produces similar results.

Table 2
Performance of institutional trading desks

		Mo.			
Current Quarter Performance Quintiles	Portfolio Formation mo.	$M+1$	$M+2$	$M+3$	$M+4$
Q1 Exec. Shortfall (%)	−0.390	−0.072	−0.057	−0.054	−0.042
Retention %	100.00	46.24	45.04	44.90	43.72
Percentile	10.63	31.15	32.07	32.24	32.93
Q2 Exec. Shortfall (%)	0.036	0.148	0.143	0.153	0.150
Retention %	100.00	29.27	28.40	27.55	27.62
Percentile	30.54	42.88	42.64	43.55	43.49
Q3 Exec. Shortfall (%)	0.241	0.251	0.250	0.248	0.249
Retention %	100.00	26.37	28.37	26.41	27.10
Percentile	50.55	50.93	50.60	50.54	50.68
Q4 Exec. Shortfall (%)	0.457	0.358	0.357	0.349	0.348
Retention %	100.00	27.96	28.39	28.65	27.07
Percentile	70.55	58.47	58.58	58.02	57.70
Q5 Exec. Shortfall (%)	0.919	0.569	0.557	0.549	0.541
Retention %	100.00	44.31	43.14	42.84	41.82
Percentile	90.42	69.21	68.34	67.83	67.46
Q5–Q1(Exec. Shortfall)	1.31	0.64	0.61	0.60	0.58
	(33.60)	(16.68)	(16.33)	(15.83)	(15.45)

This table examines the execution shortfall persistence of institutional trading desks. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions during the time period from January 1, 1999, to December 31, 2008. 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 value-weighted average execution shortfall across all tickets for each institution and month. At each month, we sort institutions into quintile portfolios based on execution shortfall. We report the average execution shortfall across all institutions in each quintile during the portfolio formation month and the subsequent four months. We also include the percentage of institutions that are in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

t-statistics in all of our analyses using standard errors clustered on institution and time period (see Moulton 1986; Thompson 2010). In further support of performance persistence, we find that the previously discussed trends continue to be significant in month $M+2$ through $M+4$, with an average Q5–Q1 difference in execution cost of sixty-one, sixty, and fifty-eight basis points, respectively.

As additional tests of performance persistence, we examine two statistics: the retention percentage (*Retention %*) and the percentile rank (*Percentile*). The *Retention %* for low-cost Q1 is the percentage of institutions ranked during month M in Q1 that continue to remain in Q1 on the basis of execution shortfall rankings in a future month. *Retention %* helps examine the breadth of good and poor persistence. If rankings based on month M have no predictive power, we expect *Retention %* for a quintile in a future month to be 20%. However, the

Retention % for the low- and high-cost quintiles in future months exceeds 40%, which suggests that past performance is informative about future performance.

A second breadth measure, *Percentile* rank, reports the average percentile rank on the basis of the execution shortfall estimated in future months for institutions ranked in a quintile during month M. By construction, the *Percentile* for low-cost Q1 (high-cost Q5) in month M is ten (ninety). If month M rankings have no predictive power, we expect the *Percentile* in a future month to be fifty. However, in future months, we find that *Percentile* for low-cost Q1 is less than fifty (below average cost) and for high-cost Q5 is greater than fifty (above average cost). Furthermore, consistent with persistent performance, the *Percentile* measure monotonically increases from the low-cost to high-cost quintile.

3.2 Multivariate analysis of persistence in institutional trading cost

Institutional trading-cost persistence could arise if some institutions initiate easier to execute tickets than do other institutions, as a result of their distinct investment models. Therefore, it is important to control for ticket and stock characteristics. Furthermore, trading costs can be influenced by market conditions, such as volatility and short-term price trends (Griffin, Harris, and Topaloglu 2003), and the market structure on the exchange that lists the stock (Huang and Stoll 1996).

Our objective is to estimate trading costs for institutions after controlling for 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; the order imbalance between buy and sell volume on the prior trading day; a variable that interacts previous day order imbalance and the buy indicator; short-term price trend, measured as the prior day's return; a variable that interacts price trend with the buy indicator; the stock's average daily volume over the prior thirty trading days; the inverse of stock price; and the ticket size normalized by the stock's average daily trading volume over the prior thirty days. We also account for institutional style by controlling for systematic differences in the type of stocks that each institution trades. As style controls, we include the stock's book-to-market quintile, momentum quintile, and firm-size quintile. Quintile rankings for these style characteristics are constructed as of the previous June, as in Daniel et al. (1997, hereafter DGTW).[10]

[10] Our results are robust to the following alternative specifications: 1) an alternative model using the log of normalized ticket size to account for possible nonlinearity; 2) adjusting the dependent variable for market-wide movement, following Keim and Madhavan (1995), by subtracting the daily return on the S&P 500 index from the ticket's execution shortfall after accounting for the ticket's direction; 3) calculating execution shortfall benchmarked against the stock's opening price on the ticket's placement date instead of the stock price when the broker receives the ticket; and 4) an examination of persistence separately for money managers and pension funds in our sample.

We evaluate the performance of trading desks, holding the ticket, the stock, and market condition measures at a common, economically relevant level. Every continuous explanatory variable is standardized to have a mean of zero and standard deviation of one so that the reported standardized coefficients can be interpreted as the impact on trading costs for a standard-deviation change in the explanatory variable. The dependent variable is not standardized and is retained in its original and economically relevant metric. Thus, each institution's fixed-effect coefficient can be interpreted as the average monthly trading cost for the institution, which is evaluated at the monthly average of each explanatory variable. We term the institution fixed effect as the institution's *trading alpha*, since the cross-sectional variation in these coefficients can be attributed to, at least in part, the skill of the trading desk. In this context, it is important to note that a higher trading alpha implies higher abnormal trading costs and consequently poor performance for a trading desk.

In Table 3, Panel A, we report the average standardized coefficient across 120 monthly regressions, the Fama–MacBeth t-statistics and p-values that are 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 are usually statistically significant; the exception being the stock's momentum and size ranks, which are not significant at the 5% level.[11] Trading costs increase by nine basis points for every standard-deviation increase in stock volatility, reflecting the higher cost of a delayed trade and the higher risk of liquidity provision, but costs decline with the stock's trading volume. Consistent with prior work, we also find that 1) trading with (against) the previous day's price trend increases (reduces) trading cost (see Wagner and Edwards 1993); 2) seller-initiated tickets are more expensive to complete than are buyer-initiated tickets; 3) NYSE-listed stocks are cheaper to trade than are NASDAQ stocks; and 4) trading costs increase with relative ticket size.

In Panel B of Table 3, we report on the tests of persistence in trading alpha, following the approach outlined for the unadjusted data in Table 2. A notable difference between the two tables is the reduction in the spread during the portfolio formation month between low- and high-cost institutions. This difference, which was 131 bp in Table 2, is reduced to ninety-one basis points in the regression framework. Despite the reduction in spread across quintile portfolios, our conclusions on the performance of trading desks remain unchanged. In future month $M + 1$, the difference in trading alphas between low- and high-cost institutions is fifty-seven basis points (t-statistic of difference = 18.06), which is similar to the sixty-four basis points reported in Table 2. Persistence is also of similar magnitude for future months $M + 2$

[11] The positive (and insignificant) regression coefficient on firm size in specifications that control for trading volume is an established finding in microstructure research (see, e.g., Stoll 2000). Prior research has attributed this relation to the high correlation between trading volume and firm size.

Table 3
Panel A: Institution fixed effect regressions of execution shortfall

	Parameter (avg.)	t-statistics (F–M)	p-value (F–M)	Positive coefficients (%)
No. of mo.	120			
Stock Volatility (Abs. value of daily return)	0.00090	19.39	.000	0.98
Market Volatility (Abs. value of daily S&P 500 return)	−0.00014	−4.51	.000	0.35
Buy dummy	−0.00060	−3.01	.003	0.41
Order imbalance (prev. trading day, $)	0.00002	0.77	.443	0.57
Order imbalance (prev. trading day, $) * Buy dummy	−0.00010	−2.12	.036	0.36
Prev. day's return	−0.00052	−6.76	.000	0.13
Prev. day's return * Buy dummy	0.00090	6.17	.000	0.79
Log (Avg. previous 30 day volume)	−0.00024	−9.04	.000	0.18
NYSE stock dummy	−0.00027	−7.17	.000	0.24
1/Price	0.00033	9.43	.000	0.83
Ticket Size/Avg. previous 30 day Volume	0.00007	5.39	.000	0.78
Book/Market quintile (previous June)	−0.00003	−3.44	.001	0.28
Momentum Quintile (previous June)	0.00000	0.01	.990	0.53
Size quintile (previous June)	0.00004	1.77	.079	0.56
Adjusted R^2	0.0272			

This table reports standardized coefficient estimates from monthly institution fixed-effects regressions of execution shortfall on economic determinants of execution shortfall. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions during the time period from January 1, 1999, to December 31, 2008. The dependent variable, *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). The regressions use the following independent variables: *Stock Volatility* is the absolute value of the daily stock return; *Market Volatility* is the absolute value of the daily S&P 500 return; *Buy Dummy* equals one for buy tickets and zero for sell tickets; *Order Imbalance* is the daily buyer-initiated minus seller-initiated dollar volume of transactions scaled by the total dollar volume on the previous day; *Prev. Day's Return* is the daily stock return on the previous trading day; *Log (Avg. previous 30 day volume)* is the natural logarithm of the average volume over the past thirty trading days; *NYSE Stock Dummy* equals one for NYSE stocks and zero otherwise; *Price* is the closing stock price on the previous trading day; *Ticket Size* is the number of shares that are executed in the ticket; and *Book/Market Quintile*, *Momentum Quintile*, and *Size Quintile* are quintile assignments for each stock based on NYSE quintile breakpoints as of the previous June. Daily stock returns, daily S&P returns, daily stock volumes and market values are obtained from the CRSP database. Dollar imbalances are calculated using TAQ data, and trades are assigned as buyer or seller initiated using the Lee and Ready (1991) algorithm. Right-hand-side continuous variables (*Stock Volatility, Market Volatility, Order Imbalance, Prev. Day's Return, Log (Avg. previous 30 day volume), Ticket Size* and *1/Price*) are standardized to have a mean of zero and standard deviation of one. We estimate the regression model for each of the 120 months in our sample and present the average coefficients across 120 months and the Fama–MacBeth t-statistics and p-values associated with the coefficients.

Table 3
Panel B: Persistence in monthly institutional trading alpha

Current Quarter Performance Quintiles		Portfolio Formation mo.	Mo. M + 1	M + 2	M + 3	M + 4
Q1	Trading Alpha (%)	−0.324	−0.165	−0.154	−0.154	−0.136
	Retention %	100.00	55.98	54.69	54.43	51.73
	Percentile	10.63	25.46	26.45	26.43	28.00
Q2	Trading Alpha (%)	0.001	0.055	0.047	0.052	0.051
	Retention %	100.00	32.53	32.00	31.46	30.70
	Percentile	30.54	41.15	40.95	41.54	41.42
Q3	Trading Alpha (%)	0.141	0.139	0.145	0.146	0.141
	Retention %	100.00	33.09	32.90	31.62	30.21
	Percentile	50.55	50.97	51.66	51.62	51.28
Q4	Trading Alpha (%)	0.279	0.225	0.219	0.216	0.210
	Retention %	100.00	32.43	31.25	30.00	29.90
	Percentile	70.55	60.57	59.83	59.46	58.94
Q5	Trading Alpha (%)	0.590	0.406	0.388	0.386	0.382
	Retention %	100.00	52.10	49.70	49.94	49.64
	Percentile	90.42	73.78	72.45	72.29	71.77
Q5–Q1 (Trading Alpha)		0.91	0.57	0.54	0.54	0.52
		(29.18)	(18.06)	(17.13)	(17.06)	(16.23)

This table examines the persistence of monthly institutional *trading alpha*. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions during the time period from January 1, 1999, to December 31, 2008. Trading alpha is estimated for each institution in each month using the cross-sectional regression presented in Table 3, Panel A. All independent continuous variables (*Stock Volatility, Market Volatility, Order Imbalance, Prev. Day's Return, Log (Avg. previous 30 day volume), Ticket Size,* and *1/Price*) are standardized to have a mean of zero and standard deviation of one, and the regression includes dummy variables for each institution. The coefficient estimate on institution dummy variables is the institution's trading alpha. Each month we sort institutions into quintile portfolios based on their trading alpha estimates. We report the average trading alpha across all institutions in each quintile during the portfolio formation month and the subsequent four months. We also include the percentage of institutions that are in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

through $M + 4$, suggesting that the conclusions from Table 2 are robust to controlling for trade difficulty.[12,13] Finally, we note that the evidence based on breadth measures (retention and percentile) of trading-desk persistence is stronger in the regression framework.

[12] We find that trading alphas are persistent in sample periods before and after decimalization. However, the Q5–Q1 spread in month *M+1* decreases from seventy-six basis points before decimalization to forty-nine basis points after decimalization.

[13] The institution fixed-effects specification precludes the inclusion of institution-specific style variables. We therefore classify Ancerno institutions into types similar to Bushee (1998, 2000) and test for persistence within each institution type. Overall, persistence results for each of the institution types are consistent with those reported in Table 3. Persistence results for institutions with low Dedicated scores or high Transient scores are marginally smaller than results for institutions that are more Dedicated or less Transient; however, all persistence results are economically meaningful and statistically significant. Overall, we do not find that institution style is driving our persistence results.

One striking finding is that the coefficients for low-cost institutions are robustly *negative* in future months $M+1$ through $M+4$, averaging between -16 and -13 basis points. A persistent pattern of negative trading costs suggests that some trading desks can contribute to portfolio performance by consistently obtaining executions at prices better than their pre-trade benchmarks. Keim and Madhavan (1997), among others, note that institutions can obtain negative trading costs by supplying liquidity.

An active mutual fund literature has long debated the ability of professional fund management to produce returns above their benchmarks, with many of these articles documenting outperformance, at least among a subset of managers. A natural question to ask is how trading alpha is related to this portfolio return literature. Do our findings suggest that some portion of fund performance persistence can be attributed to the activities of the buy-side trading desk?

4. Trading Cost and Portfolio Performance

In the previous analysis, we document that the difference in execution costs between low- and high-cost institutions is economically large, at around fifty-seven basis points per ticket. Ceteris paribus, these results should directly contribute to the relative performance of institutional portfolios. However, the question becomes more nuanced when we ask whether trading alpha is related to the abnormal holding-period returns of securities that an institution buys and sells (*portfolio performance*). Here, we wish to compare execution skill with the stock-selection ability of the institution. The correlation between execution skill and portfolio performance could be positive if certain institutions are skilled in both trade execution and security selection. This supports the idea that institutions that invest resources in developing execution abilities also invest in generating better investment ideas. Another possibility is that informed traders incur high trading costs in order to exploit short-lived private information. Thus, if the value of private information is large enough to overcome the price impact of their trades, the correlation between execution skill and portfolio performance could be negative.

We compare the future performance of the stocks actually bought and sold by an institution to the performance of the institution's trading desk. Our analysis proceeds as follows: For each institution, we separate all tickets in each month into buys and sells. Then, for each buy or sell ticket, we track its performance from the execution date (using the execution price) until the closing price on day $t+1$, $t+19$, or $t+59$. Our holding-period return calculations account for both stock splits and dividend distributions. We subtract the DGTW benchmark return over the same holding period for each ticket to compute abnormal returns. DGTW benchmark returns are constructed based on size, book-to-market, and past performance, as described in Daniel et al. (1997). Next, for each institution, we separately compute the value-weighted average abnormal returns for buys and sells. Finally, we assign institutions to quintile groups on the basis of their prior-month trading alpha rank.

We report the average abnormal performance of buy tickets, sell tickets, and the difference between buy and sell tickets across all institutions in each trading-alpha quintile in Table 4. Our measure of portfolio performance—the buy-minus-sell portfolio—is consistent with Chen, Jegadeesh, and Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Puckett and Yan (2011).[14] We find that the post-trade performance of stocks traded by low-cost Q1 institutions outperforms those of other quintiles. Specifically, the twenty-day (one month) abnormal performance of buys minus sells is 0.46% for low-cost Q1 institutions versus −0.15% for high-cost Q5 institutions.[15] This monthly difference of 0.61% is statistically significant (t-statistic = 5.24). These Q5–Q1 differences are also evident when we examine alternative evaluation windows of two trading days or sixty trading days.[16,17]

The standard microstructure models predict that informed traders possess an information advantage that deteriorates with time. To the extent that Q5 institutions incur high trading costs in order to implement trading strategies that exploit their short-term information advantage, we expect to see better post-trade performance for Q5 institutions. However, the results do not support the contention that high-cost Q5 institutions have access to superior short-term information.

Our main finding is that institutions with superior execution skill also exhibit better portfolio performance. Particularly noteworthy is the increase in Q5–Q1 spread as the measurement period lengthens, suggesting that the superior

14 Chen, Jegadeesh, and Wermers (2000) contend that active stock trades represent a stronger manager opinion than do passive holdings of existing positions and argue that examining the performance of a recently traded portfolio can be a more powerful test of stock-selection skill.

15 The positive abnormal performance of both buy and sell trades in Table 4 suggests that institutions traded more heavily during this period in stocks that outperformed their benchmarks. We attribute much of this outperformance to a higher concentration of trading in technology stocks during the technology bubble. Because technology stocks outperformed DGTW benchmarks during the bubble, institutions that actively traded these stocks exhibit positive abnormal performance for both their buys and sells. To benchmark, we investigate the 2001–2008 post-bubble sample period separately and find that some quintile buy or sell trades underperformed DGTW benchmarks; however, the primary results that we report in Table 4 continue to hold for the post-bubble period.

16 Results are similar when portfolio performance is measured using raw returns. Specifically, the raw post-trade performance of low-cost Q1 institutions is thirty-one basis points (fifty-eight basis points) higher than high-cost Q5 institutions during the twenty-day (sixty-day) measurement period, and both differences are statistically significant. Thus, trade performance is related to both the raw and the risk-adjusted portfolio performance measured over monthly or quarterly horizons.

17 In robustness tests, we match a subset of 64 Ancerno institutions to their respective quarterly 13F filings. We then examine the DGTW abnormal returns of all disclosed portfolio holdings for institutions in each trading-alpha-quintile group over the quarter following portfolio formation. Our results show no significant relation between the abnormal holding-period returns of low-cost (Q1) and high-cost (Q5) institutions. However, we note three significant shortcomings of this approach: First, this analysis is limited to only a subset of 64 institutions in the database; second, our analysis of holding-period returns using end-of-quarter holdings ignores any price change that occurs between the transaction and the end of the quarter; and third, quarterly holdings do not capture intra-quarter round-trip trades where institutions buy and sell or sell and repurchase the same stock.

Table 4
Trading alpha and portfolio performance

Trading Alpha Quintiles		Next-day performance (2 trading days)	1-month performance (20 trading days)	3-month performance (60 trading days)
Q1 (low)	buy	0.216	0.443	0.498
	sell	–0.063	–0.017	–0.025
	buy – sell	*0.280 (9.79)*	*0.460 (5.09)*	*0.522 (3.28)*
Q2	buy	0.139	0.199	0.117
	sell	–0.023	0.080	0.165
	buy – sell	*0.162 (8.18)*	*0.119 (2.05)*	*–0.047 (–0.41)*
Q3	buy	0.104	0.120	0.063
	sell	0.017	0.014	–0.024
	buy – sell	*0.088 (4.65)*	*0.105(1.89)*	*0.087(0.88)*
Q4	buy	0.066	0.078	–0.075
	sell	0.059	0.112	0.099
	buy – sell	*0.007 (0.31)*	*–0.034 (–0.71)*	*–0.174 (–2.13)*
Q5 (high)	buy	0.021	0.056	–0.123
	sell	0.100	0.204	0.232
	buy – sell	*–0.079 (–2.81)*	*–0.148 (–2.07)*	*–0.355 (–3.01)*
Q5–Q1	buy	0.195 (7.91)	0.389 (3.88)	0.621 (3.66)
	sell	–0.163 (–7.71)	–0.221 (–3.56)	–0.257 (–1.94)
	buy – sell	*0.359 (9.19)*	*0.610 (5.24)*	*0.877(4.40)*

Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions during the time period from January 1, 1999, to December 31, 2008. For each ticket, we calculate the raw cumulative stock return from the execution price until the close one, nineteen, or fifty-nine trading days following the trade. We adjust the raw cumulative return by the DGTW benchmark return over the same period. For each institution in each month, we then separately compute the value-weighted DGTW-adjusted returns for buys and sells. We then take the difference in DGTW-adjusted returns between buys and sells. We report a simple average across all institutions in each quintile, where quintile assignments are based on prior-month-trading alpha-quintile rankings. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

performance of Q1 institutions is not transitory. Thus, institutions with better trading ability exhibit better stock-picking ability: Trading skill and stock-picking skill appear to be complements rather than substitutes. One possible explanation is that institutions that invest in developing investment ideas also invest in building a good trading desk.

5. Institutional Trading Persistence and Broker Performance

5.1 Multivariate analysis of persistence in broker performance

An institution's trading desk is responsible for developing guidelines for broker selection and monitoring broker performance. Brokers themselves may possess above- or below-average ability to execute trades. In this section, we examine whether brokers exhibit performance persistence. To examine broker performance, we repeat the regression analysis in Table 3, Panel A, with broker fixed effects rather than with institution fixed effects. Following prior notation, we term the broker fixed effect as the broker's trading alpha. The control regression coefficients (not reported) are similar to those reported in Table 3, Panel A.

We construct broker quintiles in portfolio formation month M by ranking the brokers each month on the basis of their trading alpha. The trading alpha for each broker quintile is presented in the portfolio formation month column of Table 5. In the portfolio formation month, the spread in broker trading alpha between the low-cost Q1 and high-cost Q5 broker quintiles is eighty-six basis points. In future month $M+1$ to $M+4$, low-cost Q1 brokers outperform high-cost Q5 brokers by approximately twenty-seven to twenty-three basis points, respectively. Furthermore, the trading alpha for the low-cost Q1 brokers, at approximately −6 bp, is insignificantly different from zero for all future months. Surprisingly, it appears that low-cost brokers can execute tickets initiated by institutions with little price impact. Other tests based on

Table 5
Persistence of monthly broker trading alpha

Current Quarter Performance Quintiles		Portfolio Formation mo.	Mo. $M+1$	$M+2$	$M+3$	$M+4$
Q1	Trading Alpha (%)	−0.346	−0.070	−0.063	−0.055	−0.048
	Retention %	100.00	44.16	42.67	41.80	41.29
	Percentile	10.71	35.88	36.15	37.72	37.59
Q2	Trading Alpha (%)	0.011	0.090	0.085	0.082	0.081
	Retention %	100.00	27.46	27.28	27.68	26.10
	Percentile	30.58	47.05	47.07	47.00	47.37
Q3	Trading Alpha (%)	0.127	0.133	0.125	0.124	0.123
	Retention %	100.00	31.50	29.73	29.35	27.93
	Percentile	50.58	52.17	52.03	52.15	52.30
Q4	Trading Alpha (%)	0.234	0.157	0.151	0.150	0.141
	Retention %	100.00	28.24	27.48	26.99	26.40
	Percentile	70.57	55.93	55.87	55.61	54.93
Q5	Trading Alpha (%)	0.519	0.202	0.199	0.184	0.185
	Retention %	100.00	34.81	33.82	32.70	32.08
	Percentile	90.37	60.45	60.21	58.83	59.18
Q5–Q1 (Trading Alpha)		0.86	0.27	0.26	0.24	0.23
		(24.25)	(7.90)	(7.56)	(6.64)	(6.55)

This table examines the persistence of monthly broker trading alpha. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed with 1,216 brokers during the time period from January 1, 1999, to December 31, 2008. Trading alpha is estimated for each broker in each month using the cross-sectional regression approach presented in Panel A, Table 3. All independent continuous variables (*Stock Volatility, Market Volatility, Order Imbalance, Prev. Day's Return, Log (Avg. previous 30 day volume), Ticket Size,* and *1/Price*) are standardized to have a mean of zero and standard deviation of one, and the regression includes dummy variables for each broker. The coefficient estimate on broker dummy variables is the broker's trading alpha. Each month, we sort brokers into quintile portfolios based on their trading alpha estimates. We report the average trading alpha across all brokers in each quintile during the portfolio formation month and the subsequent four months. We also include the percentage of brokers that are in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile brokers (*Percentile*). Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

Retention% and *Percentile* also support the hypothesis that broker performance is persistent. For example, 41% of the brokers categorized as low-cost in month M are also independently ranked as low-cost in future month $M+4$.

All of our persistence results are robust to the length of the periods examined. Specifically, the spread between the low- and high-cost performers is significant in future months $M+5$ to $M+12$. In month $M+12$, the spread for institutional desks is forty-five basis points (t-statistic $= 13.55$) and for brokers is nineteen basis points (t-statistic $= 5.72$). Figure 1 plots these results up to month $M+12$. We also estimate all-in trading costs that include both the explicit (commissions) and implicit (trading alpha) trading costs and find a similar spread between low- and high-cost performers. For institutional trading desks (brokers), the Q5–Q1 differential in all-in trading costs is fifty-six basis points (twenty-eight basis points) in month $M+1$and fifty basis points (twenty-five basis points) in month $M+4$.[18]

5.2 The interplay between institutional desks and brokers

In Table 6, we present descriptive statistics on the interplay between institutional desks and brokers. Specifically, we examine the extent to which broker characteristics differ for low- and high-cost institutions (Panel A) and whether brokers provide better executions for their important institutional clients (Panel B). For each broker (in each month), we calculate a *Broker Specialization* and a *Broker Concentration* index.[19] *Broker Specialization* is a broker's Herfindahl index based on trading volume executed across forty-eight Fama–French industries, while *Broker Concentration* is a broker's Herfindahl index based on the distribution of trading volume across institutions (i.e., more concentrated brokers derive more volume from fewer institutions). For each institution, we then calculate a value-weighted average *Broker Specialization* and *Broker Concentration* index across all brokers that an institution uses in a month and report a simple average across institutions in each trading alpha quintile. Panel A reveals that low-cost Q1 institutions employ brokers with slightly higher *Broker Specialization* and higher *Broker Concentration*, relative to high-cost Q5 institutions, but the differences are not significant at the 5% level. In an unreported analysis, we estimate that the average Q1 institution uses approximately two more brokers than the average Q5 institution. However, the number of brokers does not monotonically decrease across trading alpha quintiles and is not statistically different between low- and high-cost institutions.

18 In untabulated robustness tests, we examine trading-alpha persistence for twenty-four months following portfolio formation and find that the Q5–Q1 trading-alpha spread for institutional quintiles in month $M+24$ is thirty-seven basis points.

19 We were told by several practitioners that some brokers specialize in particular stocks or industries. These brokers tend to be better informed about hidden pools of liquidity in their stocks. The concentration of institutional trading and commission rates are based on cross-sectional differences in Goldstein et al. (2009).

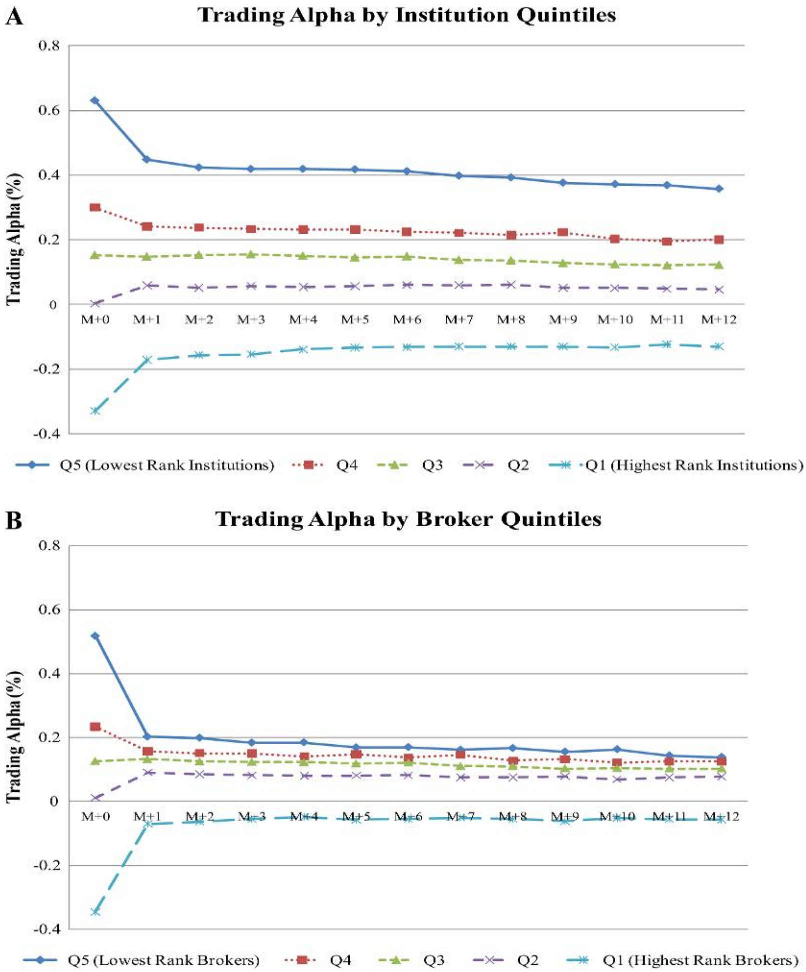

Figure 1
Institutional and broker trading alphas
Figure 1 presents the monthly time series of trading alphas (%) for institutional trading desk (Panel A) and broker (Panel B) quintiles. Quintiles are formed each month, and trading-alpha estimates for each quintile are presented for the portfolio formation month ($M+0$) and subsequent twelve months. Trading-alpha estimates for each institutional trading-desk (broker) quintile are obtained by using an identical methodology to that presented in Table 3, Panel B (Table 5).

In addition to choosing brokers, institutional desks face myriad choices that involve the payment of explicit commissions.[20] We examine whether brokers expend more effort when explicit commissions paid to the broker are higher.

[20] Explicit commission payments and broker selection are likely to be highly correlated in cases involving low-touch brokerage firms (i.e., ECNs). However, rapid changes in the brokerage industry have also facilitated a marketplace in which both high- and low-touch executions are available within the same brokerage firm.

Table 6
Institutions and brokers

Panel A: Univariate differences

	Institution Trading Alpha Quintiles						
	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	t-stat
Broker Specialization	0.1092	0.1017	0.1010	0.1021	0.1037	−0.0055	(1.31)
Broker Concentration	0.2410	0.2285	0.2325	0.2369	0.2295	−0.0115	(1.89)
Commissions (cents)	0.0362	0.0347	0.0349	0.0347	0.0347	−0.0015	(1.93)
Commissions (%)	0.1395	0.1204	0.1164	0.1166	0.1199	−0.0195	(3.62)

Panel B: Impact of an institution's importance to a broker

	Importance Quintiles						
	I1	I2	I3	I4	I5	Diff (I5–I1)	t-stat
Importance	4.853%	0.928%	0.437%	0.216%	0.100%		
I-B Trading Alpha	0.122%	0.125%	0.162%	0.189%	0.215%	0.093%	(5.63)
I-B Rank	2.961	2.971	3.009	3.031	3.053	0.092	(4.57)

This table presents statistics on how institutions interact with brokers. For each broker (in each month), we calculate a *Broker Specialization* Herfindahl index based on trading volume executed across forty-eight Fama–French industries and a *Broker Concentration* Herfindahl index based on the distribution of trading volume across institutions. We then calculate a value-weighted average *Broker Specialization* and *Broker Concentration* index for each institution across all brokers that an institution uses in a month and a value-weighted average of explicit commission paid (in cents per share and in basis points) for each institution each month. We report a simple average across all institutions in each trading-alpha quintile and differences between extreme trading-alpha quintiles in Panel A. Panel B presents analyses on whether execution costs vary based on a client's importance to a broker. *Importance (i,b)* for each institution (i)–broker (b) pair (I–B pair) is the total dollar commissions received by broker (b) from institution (i) in a month divided by the total dollar commissions received by broker (b) in the month. For each portfolio formation month, we calculate trading alpha using the same set of controls as in Table 3, Panel A, for each I-B pair and the *I-B trading alpha rank,* which is the institution's quintile rank based on I–B trading alpha within a broker. We sort the institutions associated with a broker into quintile portfolios based on *Importance (i,b)* and report the average *I-B trading alpha* and the average *I-B (trading alpha) rank* for each *Importance (i,b)* quintile. Numbers in parentheses are t-statistics.

To test whether execution quality is related to commissions, we calculate the volume-weighted average of explicit commission paid (in cents per share and in basis points) for each institution each month. We then report a simple average across all institutions in each trading-alpha quintile. We find that Q1 institutions pay moderately higher commissions (in cents per share and in percent) than do Q5 institutions, suggesting that execution quality is related to broker compensation. The commission differences are, while statistically significant, small in magnitude (less than two basis points), especially when compared with the Q5–Q1 trading-alpha difference reported in Table 3.

Panel B presents additional analyses on whether execution costs vary on the basis of a client's importance to a broker. *Importance (i,b)* for each institution (i)–broker (b) pair (I–B pair) is the total dollar commissions received by broker (b) from institution (i) in a month divided by the total dollar commissions received by broker (b) in the month. We sort institutions associated with each broker into quintile portfolios on the basis of *Importance (i,b)*. The within-broker quintile rank standardizes the relative importance of institutions for a broker and enables aggregation across brokers. We find that an institution ranked as most important (I1) contributes about 4.85% of the broker's monthly commission, while an institution ranked as least important (I5) contributes only 0.10% of the broker's monthly commissions. The patterns suggest that quintile ranks are informative about the institution's importance to a broker.

We examine whether execution costs vary on the basis of the institution's importance to a broker. For each portfolio formation month, we calculate trading alpha by using the same set of controls as in Table 3, Panel A, for each I–B pair. We report the average I–B trading alpha and the average I–B trading-alpha rank. The I–B trading-alpha rank is the institution's quintile rank that is based on the I–B trading alpha. The I–B trading-alpha rank is directly comparable across brokers but lacks the intuitive appeal of the alphas themselves. While we do not attribute causality on the basis of these results, both measures indicate that more important institutions are associated with better execution quality.

5.3 The joint performance of institutional desks and brokers

Trading performance is a joint production problem, as it takes both a broker and an institutional desk to execute a ticket. We show that both institutional desks and brokers exhibit persistence in relative performance. The difference between the low- and high-cost performers is economically large enough to have considerable influence on measures of portfolio performance. Because institutions choose brokers, one possibility is that the trading desks that select better brokers benefit from their selection such that much of institutional performance is an artifact of broker trading skill.

Alternatively, since the $M+1$ difference in institutional trading alpha (at fifty-seven basis points) is more than twice the difference in broker trading alpha (at twenty-seven basis points), it is possible that institutional desks add value beyond the selection of better brokers. More important may be the dynamic decisions being made by the trading desk relating to the *timing* and *sequence of release* of the order to brokers, the choice of trading venue, and instructions to brokers on how to work the order. These instructions are based on the broker's expertise on specific types of executions, the broker's willingness to commit capital, the type of stock being traded, and importantly, the market conditions when the order is being worked.[21]

We disentangle the broker's contribution to institutional trading alpha by using several different techniques that exploit ticket-level data on institution and broker identities. The first approach that we use compares an institution's trading alpha with the weighted average trading alpha of brokers that the institution employs to execute its trades, where the weights are the proportion of dollar trading volume routed to a broker. We call this weighted average the *broker implied alpha*. If trading-desk performance reflects only broker

[21] Our conversations with institutional traders suggest that trading desks rarely disclose more than 10% of a large order at any point in time to a single broker. Thus, brokers rarely have full information on the size of the order.

selection, our tests should find relatively little difference between institutional trading alphas and broker implied alphas. We separate institutions into quintiles based on their previous month (M) trading alpha and report the month $M+1$ trading alpha, broker implied alpha, and the difference between the two in Table 7. Our findings suggest that the difference in broker implied alphas between Q1 and Q5 institutions is around four basis points. Certainly, these differences are not large enough to explain persistent differences in institutional trading alpha. The low-cost Q1 institutions outperform their broker implied alphas by twenty-six basis points, while the high-cost Q5 institutions underperform their broker implied alphas by twenty-seven basis points. This test demonstrates that differences in institutional trading alphas reflect more than just choosing different sets of brokers.

To quantify the degree of interdependence between institution and broker trading alpha, our second approach simply estimates the covariance between institutional trading costs and the costs of the brokers that the institution employs. For each portfolio formation month, we calculate trading alpha by using the same set of controls as in Table 3, Panel A, for each I–B pair. This cost is designated as C_{ibt}. Since institutional performance is the sum of broker performance for the institution, the weighted average of C_{ibt} will sum to the institution's trading alpha in a particular month. For each institution-month, we run the following regression:

Table 7
Comparison of institution alpha and broker implied alpha

	Trading Alpha Quintile Rankings Based on Month M				
	(Low Cost) Q1 (%)	Q2 (%)	Q3 (%)	Q4 (%)	(High Cost) Q5 (%)
Institution Trading Alpha in Month $M+1$	−0.164	0.055	0.139	0.224	0.406
Value-Weighted Broker implied Alpha	0.096	0.126	0.131	0.136	0.139
Difference	−0.261	−0.071	0.008	0.088	0.266
	(−15.00)	(−10.01)	(1.44)	(12.93)	(15.37)
Equal-Weighted Broker Implied Alpha	0.086	0.118	0.124	0.129	0.136
Difference	−0.250	−0.064	0.015	0.095	0.270
	(−14.83)	(−9.22)	(2.65)	(13.96)	(15.57)

This table compares an institution's trading alpha to the average trading alpha of brokers that the institution employs to execute its trades. We term this average the *broker implied alpha*. For each institution, we obtain trading-alpha estimates in each month using the methodology presented in Table 3. In order to obtain *broker implied alphas*, we first obtain broker trading alphas in each month (as in Table 5). Next, for each institution and month, we compute the value- or equal-weighted broker trading alpha across all brokers that the institution uses to execute trades in that month. Value-weighted construction is based on the dollar value of trading volume that is routed to each broker. We report an average trading alpha, *broker implied alpha,* and difference between the two across all institutions in each trading-alpha quintile, where quintile assignments are based on prior-month trading-alpha-quintile rankings. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

$$C_{ibt} = a + bC_{bt} + \varepsilon. \tag{2}$$

In regression equation (2), C_{bt} is the broker's trading alpha (as in Table 5) that is based on tickets from all institutions that use broker b. The intercept a estimates the part of the institution i's trading alpha that is uncorrelated with broker performance, which we denote as "*institution-only*" trading alpha. Furthermore, the R^2 from the regression estimates the total variation in the joint institution-broker performance that can be explained by broker performance. If institutional trading alpha is an artifact of broker selection, we expect that much of the variation in an institution's performance can be explained by the choice of the broker; the intercept, a, should be zero, and the R^2 of the regression should be close to one.

The estimation of Equation (2), reported in Table 8, finds that broker performance has only a modest impact on institutional trading alpha. Across all institutions and sample months, the mean R^2 from estimating Equation (2) is 5.56%, confirming that broker performance does not explain much of the variation in institutional trading alpha.

Our results thus far do not preclude the possibility that broker performance explains significant variation in trading alpha for the subset of institutions with high R^2 values. In order to examine whether broker trading performance significantly attenuates institutional trading-alpha persistence for part of our sample, we split our sample into two groups: institution-months with below-median R^2 and those with above-median R^2. For each R^2 group, we assign institutions to quintile portfolios based on their trading alpha during the portfolio formation month (month M) and report both the trading alpha (from Table 3, Panel B) and *institution-only* trading alpha in month $M+1$. In both R^2 groups, we find an economically significant spread in both trading alpha and *institution-only* trading alpha. The difference in trading alpha between Q1 and Q5 institutions is similar across low and high R^2 groups, at fifty-eight basis points for the low R^2 group and fifty-five basis points for the high R^2 group. For *institution-only* alphas, which are statistically independent of broker performance, we find that the difference between high- and low-cost institutions is sixty-one basis points in the low R^2 group and forty-seven basis points in the high R^2 group. From this statistical examination of broker influence on institution trading alpha, we conclude that institutions' trading desks appear to add significant value beyond broker selection.

We assess the economic significance of institution rank and broker rank on trading costs in Table 9, where we run a ticket-level regression of execution shortfall on firm characteristics, order characteristics, and market conditions (similar to Table 3, Panel A). In addition, we include the institution's prior-month quintile rank (RI) from Table 3 and the broker's prior-month quintile rank (RB) from Table 5, which are associated with each ticket as explanatory variables. The analysis in Table 9 helps assess the economic significance of

Table 8
"Institution-only" trading alpha

	Full Sample			Low R^2 Group			High R^2 Group		
	Inst.-only Alpha	Trading Alpha	R^2%	Inst.-only Alpha	Trading Alpha	R^2%	Inst.-only Alpha	Trading Alpha	R^2%
Q1	−0.212	−0.149	5.52	−0.190	−0.174	0.86	−0.222	−0.145	10.53
	(−11.36)	(−17.87)		(−7.33)	(−6.87)		(−8.83)	(−6.06)	
Q2	−0.018	0.055	5.44	0.035	0.050	0.86	−0.090	0.054	10.50
	(−1.77)	(3.79)		(1.83)	(3.19)		(−3.98)	(3.04)	
Q3	0.097	0.140	5.66	0.149	0.148	0.84	0.034	0.143	10.78
	(8.95)	(9.93)		(7.83)	(8.66)		(1.87)	(8.17)	
Q4	0.170	0.225	5.57	0.242	0.222	0.85	0.114	0.240	10.71
	(13.02)	(15.77)		(11.42)	(11.73)		(5.07)	(10.44)	
Q5	0.350	0.401	5.66	0.422	0.402	0.86	0.253	0.402	10.51
	(25.37)	(17.64)		(14.25)	(12.98)		(9.93)	(15.14)	
Q5–Q1	0.56	0.55		0.61	0.58		0.47	0.55	
	(31.69)	(21.39)		(16.16)	(16.86)		(12.80)	(16.92)	

We control for the brokers' contribution to institutional trading alpha by removing the part of institutional trading alpha that is correlated with broker performance. For each month, we calculate trading alpha using the same set of controls as in Table 3, Panel A, for each institution (i)-broker (b) pair. This cost is designated as C_{ib}. Separately, we estimate the average trading alpha for each broker b in that month (as in Table 5): C_b. For each institution, we run the following regression in each month: $C_{ib} = a + bC_b + \varepsilon$. In this regression, the intercept a estimates the component of institution i's trading alpha that is uncorrelated with broker performance. We call the estimate a the *Institution-only alpha*. The R^2 from this regression estimates the amount that broker performance contributes to the total variation in joint institution-broker trading alpha. We then split the sample into two groups: institution-months with below-median R^2 and those with above-median R^2. For the full sample and each R^2 group, we assign institutions to quintile portfolios based on their trading alpha during the portfolio formation month (month M) and report both the trading alpha (from Table 3, Panel B) and *institution-only* trading alpha in the month $M + 1$. All numbers are in percent. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

Table 9
Marginal impact of institution and broker quality

	Parameter (avg.)	t-statistics (F–M)	p-value (F–M)	Positive coefficients (%)
No. of mo.	119			
Intercept	−0.00298	−14.65	*.000*	0.03
Stock Volatility (Abs. value of daily return)	0.00091	19.46	*.000*	0.98
Market Volatility (Abs. value of daily S&P 500 return)	−0.00015	−4.38	*.000*	0.37
Buy dummy	−0.00062	−3.06	*.003*	0.40
Order imbalance (prev. trading day, $)	0.00001	0.37	*.711*	0.53
Order imbalance (prev. trading day, $) * Buy dummy	−0.00008	−1.65	*.102*	0.41
Previous day's return	−0.00055	−6.95	*.000*	0.13
Previous day's return * Buy dummy	0.00097	6.43	*.000*	0.81
Log (Avg. previous 30 day volume)	−0.00023	−7.79	*.000*	0.19
NYSE stock dummy	−0.00032	−7.77	*.000*	0.20
1/Price	0.00028	8.21	*.000*	0.79
Ticket Size/Avg. previous 30 d. daily volume	0.00008	5.65	*.000*	0.83
Broker rank	**0.00040**	**13.30**	***.000***	**0.92**
Institution rank	**0.00100**	**24.21**	***.000***	**1.00**
Book/Market quintile (previous June)	−0.00004	−4.71	*.000*	0.26
Momentum Quintile (previous June)	0.00002	1.73	*.086*	0.60
Size quintile (previous June)	0.00007	2.58	*.011*	0.66
Adjusted R^2	0.0157			

This table presents a regression that measures the marginal impact of broker and institution quality on execution costs. In this regression, the dependent variable, *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). The regressions use the following independent variables that are described in Table 3.A: *Stock Volatility*, *Market Volatility*, *Buy Dummy*, *Order Imbalance*, *Prev. Day's Return*, *Log (Avg. previous 30 day volume)*, *NYSE Stock Dummy*, *Price*, *Ticket Size*, *Book/Market Quintile*, *Momentum Quintile*, and *Size Quintile.* Daily stock returns, daily S&P returns, daily stock volumes, and market values are obtained from the CRSP database. Dollar imbalances are calculated using TAQ data, and trades are assigned as buyer or seller initiated using the Lee and Ready (1991) algorithm. Right-hand-side continuous variables (*Stock Volatility, Market Volatility, Order Imbalance, Prev. Day's Return, Log (Avg. previous 30 day volume), Ticket Size,* and *1/Price*) are standardized to have a mean of zero and standard deviation of one. The regressions also include the independent variables *Broker Rank* and *Institution Rank* in order to investigate the impact of broker and institution quality while controlling for economic determinants of execution shortfall. *Broker Rank* is the brokerage firm quintile ranking in the previous month, and *Institution Rank* is the institution quintile rank in the previous month. Broker and Institution ranks are obtained separately in each month using regression specifications presented in Tables 3.A and 5. Rankings are from 1 (lowest cost) to 5 (highest cost). We estimate the regression model for 119 months in our sample (we lose one month because we use lagged institution and broker ranks) and present the average coefficients across 119 months and the Fama–MacBeth t-statistics and p-values.

institution rank and broker rank on trading costs. The coefficient on broker rank (RB) is 0.0004 (t-statistic of coefficient = 13.30), suggesting that trading-costs for brokers, who are ranked one quintile higher on the basis of past performance, is lower by four basis points. Stated differently, the trading-cost difference between a low-cost Q1 broker and a high-cost Q5 broker is sixteen basis points. We also find that the coefficient on institution rank is larger than the coefficient on broker rank (t-statistic of difference = 17.79). In terms of economic significance, ceteris paribus, we estimate that the low-cost trading desks outperform the high-cost trading desks by approximately forty basis points.

5.4 Analysis of "stitched" ticket orders

An institutional desk typically breaks up a large order into smaller tickets and works the order over time. The timing and sequence of release of tickets to multiple brokers that span multiple days is an important dynamic decision made by the trading desk. Unfortunately, the Ancerno database does not contain information that would allow us to identify all tickets associated with a large order. We therefore implement an algorithm to "stitch" seemingly related tickets in the database into a single multiday order. Specifically, we group all tickets from the same institution across brokers on the same side of the trade (buy or sell) in a given stock over adjacent days into a stitched ticket order.[22] Tickets that are canceled with a broker, but replaced with another broker, are captured in the analysis; however, canceled tickets that are never replaced are lost. We use the opening price on the first day of the stitched order as the pre-trade benchmark price for all tickets that make up a multiday order.

Table 10 presents the persistence analysis for institutions based on stitched ticket orders. The regression specification coefficients (not reported) are similar to those reported in Table 3, Panel A. In the portfolio formation month, the spread between low-cost Q1and high-cost Q5 institutions on the basis of stitched orders is 132 bp. In future months $M+1$ to $M+4$, low-cost Q1 institutions outperform high-cost Q5 institutions by approximately seventy-seven to seventy-one basis points, respectively. In comparison, the Table 3 trading-alpha spread in month M is ninety-one basis points and the trading-alpha spread in future months is fifty-seven to fifty-two basis points. We conclude that the trading-alpha persistence that we document is robust to controlling for multiday orders.[23] In fact, the larger Q5–Q1 spread for multiday orders suggests that the dynamic timing decisions of trading desks are an important source of trading-cost heterogeneity across institutions.

The stitched-order analysis can help address some limitations of the Ancerno data. As noted earlier, canceled tickets that are replaced are captured by the analysis. Furthermore, when a ticket is canceled and replaced with a different broker at a later time, the database does not tag the replacement ticket with the benchmark price from the original ticket. In the stitched-order analysis, the benchmark price for all tickets associated with a stitched order is the opening price on the first day of the stitched order. Thus, any price drift between the stock price on the first day of the order and the stock price at ticket placement time is captured. For these reasons, the stitched-order analysis is able to appropriately reward or penalize trading desk's decisions, such as order

[22] Given that our order-stitching algorithm is an imperfect approximation of which tickets constitute an order, we truncate our sample to include trade orders that span 5 or fewer trading days. We selected five days after speaking with several professional traders on a reasonable choice for this purpose. In our sample, five days lies on the ninety-fifth percentile of the distribution of the duration for stitched orders.

[23] In an untabulated analysis, we rank institutions based on the ticket-level trading alpha (i.e., Table 3.B) and find persistence in trading-cost performance based on executions of stitched ticket orders.

Table 10
Persistence of trading alpha using multiday trade orders

			Mo.			
Current Quarter Performance Quintiles		Portfolio Formation mo.	$M+1$	$M+2$	$M+3$	$M+4$
Q1	*Trading Alpha (%)*	−0.370	−0.109	−0.106	−0.101	−0.078
	Retention %	100.00	51.91	50.97	50.73	48.14
	Percentile	10.63	27.63	28.18	28.40	29.79
Q2	*Trading Alpha (%)*	0.072	0.162	0.173	0.172	0.175
	Retention %	100.00	30.93	29.10	30.03	29.46
	Percentile	30.54	41.58	42.33	42.37	42.46
Q3	*Trading Alpha (%)*	0.276	0.276	0.276	0.281	0.274
	Retention %	100.00	28.09	27.11	26.96	27.54
	Percentile	50.55	50.29	50.37	50.49	50.03
Q4	*Trading Alpha (%)*	0.491	0.406	0.394	0.397	0.388
	Retention %	100.00	30.43	29.32	29.47	29.02
	Percentile	70.55	59.69	59.22	59.22	58.42
Q5	*Trading Alpha (%)*	0.946	0.666	0.642	0.638	0.636
	Retention %	100.00	51.11	48.09	47.88	47.63
	Percentile	90.42	73.27	72.02	71.75	71.49
Q5–Q1 (*Trading Alpha*)		1.32	0.77	0.75	0.74	0.71
		(35.95)	(19.93)	(18.77)	(18.66)	(17.96)

This table examines the persistence of monthly institutional trading alpha after "stitching" tickets into multiday orders. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions during the time period from January 1, 1999, to December 31, 2008. Our algorithm to "stitch" tickets into multiday trade orders groups tickets from the same institution, stock, and side over adjacent trading days. We truncate the sample to include trade orders that span five or fewer days. Trading alpha is estimated for each institution in each month using the cross-sectional regression presented in Panel A of Table 3. The dependent variable, *Execution Shortfall*, is measured as the buy ticket execution price minus the opening price on the first day of the trade order divided by the opening price on the first day of the trade order (for sell tickets, we multiply by −1). All independent continuous variables (*Stock Volatility, Market Volatility, Order Imbalance, Prev. Day's Return, Log (Avg. previous 30 day volume), Ticket Size,* and *1/Price*) are standardized to have a mean of zero and standard deviation of one, 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 sort institutions into quintile portfolios based on their trading-alpha estimates. We report the average trading alpha across all institutions in each quintile during the portfolio formation month and the subsequent four months. We also include the percentage of institutions that are in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

splitting and the timing and sequence of release of tickets, associated with a large order.

It is also possible that a broker's trading alpha is influenced by whether the broker is early or late in the process of executing a stitched order. This is because institutions may route the early part of an order to a discount broker and release the unfilled portions of the order to a full-service broker. The Ancerno database contains reliable information on the ticket placement date but not the ticket placement time. We are therefore unable to identify whether a broker receives a ticket early or late within the day. However, for the stitched multiday orders, we examine whether there is a systematic difference between when low-cost Q1 and high-cost Q5 brokers receive the tickets (i.e., the relative day of the stitched order) from institutions. In an untabulated test, we find no significant difference in the relative day of ticket placement between low- and high-cost brokers. We also find that low-cost institutions trade over longer horizons than do high-cost institutions, but the difference is economically small.

5.5 Institutional trading performance and broker services

Although certain institutions consistently obtain poor executions, these institutions might not violate their fiduciary best execution obligations. Goldstein et al. (2009) report that the trading arrangements between institutions and brokers often bundle execution with other broker services, such as research and profitable IPO allocations, and that commissions on bundled-execution trades are higher than they are on execution-only trades. While institutions accept higher commission costs in return for broker services, might they accept higher execution costs as well? To examine this question, we separate the 1,216 brokers in our sample into two groups: execution-only brokers and full-service brokers. Execution-only brokers include discount brokers, ECNs, market makers, and floor brokers who specialize in trade execution. Full-service brokers bundle trade execution with other services.[24]

Table 11 separately examines institutional persistence for trades executed through execution-only and full-service brokers. Using the methodology in Table 3, Panel B, we report trading-alpha persistence for execution-only trades in Table 11, Panel A, and for full-service trades in Panel B. We find that significant persistence exists for both types of trades; however, there are apparent differences across the two groups. In Table 11, Panel B, the differences between low-cost Q1 and high-cost Q5 institutions that use full-service brokers range from fifty-eight basis points in month $M+1$ to fifty-three basis points in month $M+4$. The corresponding difference for institutions that use execution-only brokers (see Panel A) is lower, ranging from forty-eight basis points in month $M+1$ to a low of forty-three basis points in month $M+4$. This difference between Panel A and Panel B is primarily explained by the presence of high-cost institutions that obtain relatively poor execution from full-service brokers (forty-five basis points in month $M+1$) compared with execution-only brokers (twenty-nine basis points in month $M+1$). While it is possible that high-cost Q5 institutions accept poor executions in return for valuable services, the fact that Q1 institutions receive excellent executions suggests that high-cost Q5 institutions could just be worse at executing their trades. Furthermore, the bulk of the persistence evidence that we document

[24] In an unreported analysis, we use a commission-based broker classification implemented by Goldstein et al. (2009). The study identifies execution-only trades as those trades where commissions charged are nonzero but less than or equal to three cents per share. Trades with commissions greater than three cents per share are identified as full-service trades. Our results are similar based on the alternative classification.

is also present in the execution-only subsample, suggesting that ancillary services do not provide a convincing explanation for our results. Moreover, from Table 4, we note that the lower portfolio performance of Q5 institutions does not support the claim that these institutions receive valuable research services from high-cost brokers, which improve investment performance.

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

If some brokers are persistently bad, then how do they survive? There is a similar debate in the mutual fund literature with regard to the question of how poorly performing index funds or money market funds survive (Elton, Gruber, and Busse 2004). In the context of our study, the high-cost brokers can survive for various reasons: 1) institutions are performance-insensitive; 2) institutional constraints on broker selection (e.g., endowments mandated to trade through custody banks); 3) capacity limitations at good brokerage houses; and 4) agency conflicts.[25] Yet another explanation is that institutions

Table 11
Persistence in monthly institutional trading alpha by broker type

Panel A: Execution-only brokers

			Mo.			
Performance Quintile		Portfolio Formation mo.	$M+1$	$M+2$	$M+3$	$M+4$
Q1	*Trading Alpha (%)*	−0.659	−0.194	−0.191	−0.170	−0.160
	Retention %	100.00	43.64	42.95	42.14	40.65
	Percentile	10.65	34.80	35.40	35.72	36.32
Q2	*Trading Alpha (%)*	−0.153	−0.048	−0.047	−0.045	−0.022
	Retention %	100.00	30.02	29.18	27.93	27.50
	Percentile	30.57	43.00	43.42	43.56	44.27
Q3	*Trading Alpha (%)*	0.050	0.054	0.055	0.062	0.045
	Retention %	100.00	31.75	31.69	30.77	30.49
	Percentile	50.57	51.51	51.29	51.45	50.84
Q4	*Trading Alpha (%)*	0.245	0.127	0.132	0.127	0.111
	Retention %	100.00	28.83	27.75	27.07	26.90
	Percentile	70.56	57.00	56.71	56.60	55.82
Q5	*Trading Alpha (%)*	0.766	0.287	0.277	0.267	0.274
	Retention %	100.00	42.24	40.63	40.87	40.21
	Percentile	90.42	65.91	64.81	64.69	64.39
Q5–Q1 (*Trading Alpha*)		1.42	0.48	0.47	0.44	0.43
		(25.19)	(16.60)	(16.79)	(15.05)	(14.43)

(*continued*)

[25] For example, in March 2008, the Securities and Exchange Commission fined Fidelity Investments for directing order flow to brokerage houses 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.

Table 11
Continued

Panel B: Full-service brokers

Performance Quintile		Portfolio Formation mo.	Mo. $M+1$	$M+2$	$M+3$	$M+4$
Q1	*Trading Alpha (%)*	−0.301	−0.128	−0.120	−0.119	−0.104
	Retention %	100.00	55.25	53.78	53.36	50.91
	Percentile	10.63	26.12	26.98	27.13	28.28
Q2	*Trading Alpha (%)*	0.037	0.093	0.092	0.090	0.093
	Retention %	100.00	32.35	30.74	31.13	30.01
	Percentile	30.54	41.47	41.80	41.88	42.15
Q3	*Trading Alpha (%)*	0.183	0.183	0.182	0.185	0.179
	Retention %	100.00	32.02	31.46	30.73	31.35
	Percentile	50.54	51.18	51.49	51.56	51.12
Q4	*Trading Alpha (%)*	0.324	0.264	0.258	0.254	0.245
	Retention %	100.00	32.49	30.77	29.19	28.05
	Percentile	70.54	59.95	59.39	59.03	58.47
Q5	*Trading Alpha (%)*	0.647	0.448	0.428	0.426	0.422
	Retention %	100.00	51.53	48.88	48.52	48.32
	Percentile	90.42	73.03	71.56	71.60	71.30
Q5–Q1 (*Trading Alpha*)		0.95	0.58	0.55	0.55	0.53
		(28.06)	(17.10)	(16.28)	(16.09)	(15.51)

This table examines the persistence of monthly institutional trading alpha for tickets that are associated with execution-only and full-service brokers. Institutional trading data are obtained from Ancerno Ltd., and the trades in the sample are placed by 750 institutions with 1,216 brokers during the time period from January 1, 1999, to December 31, 2008. We separate all tickets into two subsamples according to the type of broker executing the trade. Execution-only brokers include discount brokers, ECNs, market makers, and floor brokers who do not provide services other than execution. Full-service brokers are brokers who do provide some ancillary services bundled alongside execution services. Institutional trading alpha is estimated separately for tickets routed to each broker type in each month using the cross-sectional regression presented in Panel A of Table 3. Our regression includes dummy variables for each institution. The coefficient estimate on institution dummy variables is the institution's trading alpha. For each broker type, we sort institutions in each month into quintile portfolios based on their trading-alpha estimates. We report the average trading alpha across all institutions in each quintile during the portfolio formation month and the subsequent four months. We also include the percentage of institutions that are in the same quintile during subsequent months (*Retention %*) and the average percentile rank of quintile institutions (*Percentile*). Panel A presents results for institutional trading-alpha persistence for institutions using execution-only brokers. Panel B presents results for institutional trading-alpha persistence for institutions using full-service brokers. Numbers in parentheses are t-statistics computed using two-way clustered standard errors.

use order flow to purchase a package of nonexecution services, which would otherwise be paid for explicitly. To examine the extent to which institutional order flow is sensitive to broker performance, we run the following regression:

$$Mkt\_Share_{ibt} = \alpha_0 + \beta_0 Mkt\_Share_{ibt-1} + \sum_{T=1}^{2} \beta_T BCost_{ibt-1} + \varepsilon. \quad (3)$$

Equation (3) is a pooled cross-sectional, time-series regression, where the dependent variable is the log of the market share of institution i's trading volume executed through broker b in month t divided by the geometric average market share of all brokers for institution i in month t, as is calculated in Boehmer, Jennings, and Wei (2007). This market share variable is regressed against lagged relative market share and lagged relative execution cost for broker b ($BCost_{ibt-1}$). The latter is calculated as the difference between the trading alpha of broker b for institution i in month $t-1$ and the average trading alpha for all broker–institution pairs that execute in month $t-1$. We estimate the sensitivity of order flow to lagged broker performance for two different broker types (T): full-service brokers (B_1) and execution-only brokers (B_2).

Estimation of Equation (3) shows that an institution's order flow to a particular broker is highly persistent; the coefficient on lagged market share is 0.58 and strongly significant. We also find that the substitution effect attributable to broker costs is negative, statistically significant, and economically small. For full-service brokers, the B_1 coefficient is -0.57 (t-statistic $= -5.03$), indicating that high relative costs decrease the market share of poorly executing brokers. However, estimated at the median absolute deviation in broker costs of fifty basis points, the reduction in volume directed to a typical poorly performing broker averages only 0.29% of their institutional allocation. The coefficient on execution-only brokers (B_2) at -1.69 (t-statistic $= -6.06$) is more than three times the magnitude of the full-service broker's coefficient, indicating a reduction in a poorly performing broker's volume of 0.84% of their institutional allocation.

The difference in the substitution effect across different broker types makes economic sense. Full-service execution is bundled with other services that the institution values and is reluctant to lose. Goldstein et al. (2009) note that the typical full-service broker/institution arrangement is long-term and therefore unlikely to be re-evaluated on a month-to-month basis. In contrast, execution-only broker order flow can be redirected without the loss of ancillary broker services. We conclude that execution costs do provide a competitive advantage to brokers. However, these forces are weak, particularly for full-service brokers, and poorly performing brokers only slowly lose market share.

6. Discussion and Implications

We note that execution costs represent a necessary expense that is associated with the implementation of investment ideas. Consequently, investment firms should be concerned about execution quality, since the cumulative impact of execution costs can dramatically affect the returns to a fund's long-term investor. Indeed, Wermers (2000) estimates that execution costs reduce the average mutual fund's gross return by eighty basis points per year. We find significant heterogeneity in institutional trading costs, suggesting that the expense of execution is not equally borne by all institutional investors. Moreover, the trading cost difference between low- and high-cost institutions is persistent, and the magnitude of the two-way trading-cost difference—at approximately 110 bp—is economically large.

We also show that the trades of low-cost institutions outperform those of high-cost institutions by 0.88% in the quarter following their trades. Our results on the performance difference between institutional buys and sells are consistent with the magnitudes reported by Chen, Jegadeesh, and Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Duan, Hu, and McLean (2009). For example, Kacperczyk, Sialm, and Zheng (2005) find that institutional buys outperform institutional sells by 1.06% in the quarter following trading activity, whereas Duan, Hu, and McLean (2009) find a performance difference in decile portfolios of 1.21%. An important contribution our study makes to the literature is the empirical link between an institution's portfolio performance and the execution abilities of an institution's trading desk. The magnitude of the trading-alpha spread between low- and high-cost trading desks suggests that it would be difficult for an institution to outperform if the portfolio manager is not supported by a strong trading desk.

While database limitations prevent a direct empirical link between trading performance and realized fund returns, we attempt to provide a comparison by referring to several recent studies in the mutual fund performance persistence literature. Perhaps the most influential study on mutual fund performance persistence is by Carhart (1997), who shows that persistence in superior fund performance is weak to nonexistent after controlling for the momentum effect. However, even Carhart (1997) finds significant differential performance between the best and worst decile of past-performing funds of around 3.48% in the year following portfolio formation. More recent studies show significant performance persistence for both the best *and* worst past-performing funds by using Bayesian estimates (Busse and Irvine 2006), bootstrap approaches (Kosowski, Timmerman, Wermers, and White 2006), or daily fund returns (Bollen and Busse 2005). These recent studies find that the best funds can achieve abnormal performance as large as between 3.8% and 5.8% a year, but the majority of funds have considerably smaller or insignificant outperformance. Although there are many unobservable factors that contribute to differential fund performance, the magnitude of the difference in trading alpha between low- and high-cost institutions is large enough to potentially explain a significant fraction of differential performance, as documented by prior literature. If, on average, funds have a turnover rate of 100%, then the *round-trip* cost difference of 110 bp is a reasonable approximation of the impact of trading cost on performance.

We also 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 $700 million if institutions route order flow to low-cost brokers instead of high-cost brokers.[26] While this estimate

[26] The average high-cost Q5 broker in our sample executes roughly $760 million each month or $9.12 billion annually. There are approximately thirty brokers in the Q5 quintile in a typical month. Thus, the Q5 quintile brokers execute roughly $274 billion each year. In Table 5, we estimate that low-cost brokers outperform high-cost brokers by about twenty-seven basis points. For the high-cost Q5 broker quintile alone, institutions choosing

is no doubt imprecise, the magnitude of the estimate emphasizes that broker selection on the basis of past performance represents an important dimension of the fund's fiduciary obligation. Yet, we find that order routing decisions are highly persistent and that poorly performing brokers only slowly lose market share. One possible explanation that we discuss in Section 5.6 is that trades are routed to certain brokers in order to purchase research-related services. Fund managers have a conflict of interest when they use resources that are being paid from a fund's assets to purchase research that the investment advisors would otherwise have to pay for themselves.[27] If advisors select brokers for reasons other than execution quality, fund investors incur the higher explicit (commissions) and implicit (execution quality) cost that is associated with using an inefficient broker. Our study presents an approach to quantify these difficult-to-observe costs and estimates the hurdle (or lower bound) on the value of soft-dollar services needed for an investment advisor to use an inefficient broker.

Currently, mutual funds are required to report standardized returns that account for the loads, fees, expenses, commissions, trading costs, and other charges. Although loads, fees, expenses, and commissions are now disclosed in the fund prospectus, a fund's transaction costs are not. We show that trading costs are large, relative to other reported costs, such as commissions and expenses.[28] We also show that trading performance is highly persistent and portfolio performance is positively correlated with trading performance. More disclosure on mutual funds' trading costs can help investors evaluate whether investment advisors are meeting their best execution obligations. Mutual fund outperformance is elusive; a thorough documentation of costs can help investors discern the likelihood that investment performance is strong enough to overcome these costs.

7. Conclusion

Trading desks are an important group of financial intermediaries that are responsible for trillions of dollars in trade executions each year. Using a proprietary database of institutional investors' equity transactions provided by Ancerno Ltd., we investigate the performance of institutional trading desks.

low-cost Q1 brokers can obtain savings of approximately $740 million. A similar approach can be used to estimate dollar savings for other broker quintiles.

27 Section 28(e) of the Exchange Act provides a safe harbor provided "the advisor determined in good faith that the amount of the commissions was reasonable in relation to the value of the brokerage and research services received." See Securities and Exchange Commission (2008) for a discussion regarding the conflicts of interest and guidance regarding the duties and responsibilities of the fund's Board of Directors with respect to the fund's trading practices.

28 The SEC's position is articulated in SEC (2003) Concept Release on "Measures to Improve Disclosure of Mutual Fund Transaction Costs." A WSJ article dated March 1, 2010, titled "The Hidden Costs of Mutual Funds," presents arguments in favor of increased transparency, emphasizing that "portfolio managers can rack up steep expenses buying and selling securities, but that burden isn't reflected in a fund's standard expense ratio."

We document significant heterogeneity in institutional trading costs and show that low-cost trading desks can consistently outperform high-cost trading desks over time. We find that some brokers can deliver better execution performance over time but that trading-desk performance is not simply limited to the selection of better brokers. These results highlight the importance of the dynamic decisions of the buy-side trading desk, including the timing and sequence of release of orders to brokers, the selection of brokers, and the monitoring of broker performance. We also find that trading skill is positively correlated with the performance of an institution's traded portfolio.

This study should also be of interest to money managers, trading desks, regulators, and investors. The magnitude of Q5–Q1 trading-alpha spread emphasizes that the skill of the trading desk can in a significant way contribute to the performance of managed portfolios. The results also suggest that broker selection should be based on past broker performance. However, we do not necessarily conclude that institutions that choose high-cost brokers violate their fiduciary best execution obligation. This is because some brokers also provide a package of ancillary services to institutions (such as prime brokerage services, IPO allocations, and research). If institutions select brokers for reasons other than execution quality, our study quantifies the value of the ancillary services that is needed for institutions to justify the use of a high-cost broker. Moreover, we find that the portfolio performance of high-cost institutions is lower than those of low-cost institutions. If the benefits of ancillary services do not show up in performance, should high-cost institutions be buying these services? We leave this question for future research.

Appendix

Ancerno database of institutional trades

In this Appendix, we present a detailed description of the Ancerno Ltd. (formerly Abel/Noser Corporation) institutional trading database.[29] Our understanding of the database is the result of dozens of conversations with Ancerno over a period of more than five years. In the following description, we detail the key insights necessary to understand the data. Where appropriate, we include samples directly taken from the Ancerno database. For each client execution, the Ancerno database contains 107 different variables. For brevity, we do not list all 107 variables in this Appendix; rather, we concentrate our discussion on what we believe to be the most important variables.

Trades are sent by institutional clients in "batches" to Ancerno. Trading data for money manager clients are received directly from these clients' Order Delivery System, while the method of data delivery for pension plan sponsors is more heterogeneous. Batches can be identified by the variable *lognumber*, and institutional clients are given a unique numerical code (*clientcode*). Each observation in the Ancerno database represents an execution. Several of the key variables of interest are *clientcode*, *clientbkrcode*, *ticker*, *cusip*, *side*, *price*, and *volume*. The *clientbkrcode* allows the researcher to identify the broker who executes the trade. *Ticker* and *cusip* identify the

29 Information in this Appendix is an updated version of Puckett and Yan (2011).

stock that is traded. *Side, price,* and *volume* identify whether the trade is a buy or sell, the execution price, and the number of shares executed.

Executions are often part of larger ticket orders that are submitted by an institution. The variables *xv* and *xp* correspond with the executed volume and volume-weighted execution price of the ticket order. Each observation (execution) corresponds with a ticket order.[30] The following illustration represents a ticket order from an institution (identified by *side*) to buy 600 shares of a particular stock (identified by *ticker*). The ticket is executed in two pieces: first for 200 shares and then 400 shares. *Price* is the execution price of the particular trade, whereas *xp* is the volume-weighted execution price for the entire ticket order. Because of space restrictions, we do not include all variables in this ticket order.

Ticket Order Example

tradedate	clientcode	clientbkrcode	ticker	side	volume	xv	price	xp
15707	32	521674	AZN	1	200	600	34.7620	34.8227
15707	32	521674	AZN	1	400	600	34.8530	34.8227

Ancerno also provides us with several additional data files, which contain the following three variables that can be mapped into the original dataset:

Variables added (with permission from Ancerno)	
Client type	This is the type: 1 = pension plan sponsor, 2 = money manager
Bcode	"Scrubbed" broker code
Bname	Brokerage firm name

After Ancerno receives trading data from a client, the data are "scrubbed" in order to resolve any potential (clerical) errors. Part of this "scrub" involves cleaning the broker names that are associated with each execution. Each broker is assigned a unique *Bcode* (and corresponding *Bname*). In the ticket order example, the *Bcode* that is mapped to this ticket is fifty and the *Bname* that is mapped to this ticket is "Morgan Stanley and Co." Executions that are associated with a broker name that cannot be resolved—either because the broker is missing or because a nonsensical name has been entered—are assigned a *Bcode* that is less than or equal to zero.

Database Integrity

Issues of survivorship and selection bias are of primary concern with any proprietary database, and we investigate both of these potential biases as they relate to the Ancerno trading data. There are at least three reasons why we believe that survivorship bias is not a concern in the Ancerno database. First, Ancerno representatives have directly told us that the database is free

30 Our analysis aggregates executions into ticket orders. Since there is no explicit variable that links executions to a ticket, we use an algorithm motivated by our conversations with Ancerno. The algorithm that we use is changed slightly during the 2006–2008 sample period in order to accommodate a minor change in Ancerno trade reporting. If our algorithm was perfect, we should find that the aggregate *volume* from executions is equal to the reported executed volume (*xv*) for the ticket. Our algorithm is perfect for 93% of all tickets. When the algorithm is not perfect, we use the corresponding ticket *xv*. In robustness tests, we find that all results are almost identical when we use the aggregated execution *volume* instead of the Ancerno ticket volume (*xv*) for all tickets.

of survivorship bias. Second, if the Ancerno data contain only surviving institutions, we would expect all sample institutions to be present at the end of our sample period. However, we observe that many institutions are present during a portion of the sample period but are no longer in the dataset in December 2008. Finally, the method by which the data were delivered to us prevents survivorship bias for most of the sample period. Specifically, in May 2003 we were provided with data for the sample period 1999–2002. Ancerno provided subsequent, annual updates every year thereafter. Since we already had the earlier data, Ancerno did not have the ability to retroactively delete nonsurviving institutions.

The potential selection bias that we investigate is that institutions that choose to become Ancerno's clients might systematically differ from the typical institution. Our discussions with Ancerno reveal that there are no explicit requirements (e.g., dollar size of funds managed, number of trades executed or type of institution) for an institution to become an Ancerno client. However, we recognize an implicit selection bias in that Ancerno clients only include those institutions that care enough about execution quality to pay a third-party consultant. What is less clear is whether these client institutions are systematically different from the universe of institutional investors. Because the Ancerno database contains neither the actual names nor the portfolio holdings of client institutions, a full sample comparison of institutions in the Ancerno database to institutions in the 13F universe is not possible. We circumvent this problem in two ways: First, we use

Table A1
Comparison of Ancerno institutions to all 13F institutions

Panel A: Comparison of Ancerno Subsample to 13F Institutions

	Ancerno Institutions	13F Institutions
Number of Stock Holdings	608	248
Total Dollar Stock Holdings ($ billion)	24.50	4.34
Size Decile	8.21	8.04
Book-to-Market Decile	3.84	3.80
Lagged Return Decile	5.96	5.91
Turnover Decile	6.02	5.76
Idiosyncratic Volatility Decile	4.66	4.68
Illiquidity Decile	2.72	2.91

	Ancerno Database	13F Database
Total Quarterly Stock Trading ($ million)	1,552.18	1,310.25
Size Decile	8.05	7.99
Book-to-Market Decile	3.75	3.83
Lagged Return Decile	5.84	5.85
Turnover Decile	6.71	6.18
Idiosyncratic Volatility Decile	5.27	4.98
Illiquidity Decile	2.78	2.91

Panel A statistics are based on a comparison of average characteristics for selected institutions in the Ancerno database and for all institutions in the Thompson 13F database. Statistics for the Ancerno database are obtained by matching a subset of sixty-four Ancerno institutions (by institution name) to their respective 13F filing data. The sample period is from 1999–2008. For each institution, we assign stockholdings to size, book-to-market, lagged return, turnover, idiosyncratic volatility, and illiquidity deciles on the basis of NYSE breakpoints. The decile portfolio with the smallest value of the sorting variable is assigned to decile 1. The decile portfolio with the largest value of the sorting variable is assigned to decile 10. We then calculate an average decile-rank value for each institution in each stock characteristic category and present the average decile-rank value for each sample of institutions. Panel B presents average characteristics of quarterly trading for Ancerno and 13F institutions. Quarterly trading by 13F institutions is calculated as the change in quarterly holdings, and data are obtained from the Thomson 13F quarterly institutional holdings database. Quarterly trading for Ancerno institutions are the aggregate net trading position of all trades within the quarter. Stock characteristic decile ranks are assigned as in Panel A. We then calculate an average decile-rank value for each institution in each stock characteristic category and present the average decile-rank value for each sample of institutions.

a list of sixty-four client institution names that Ancerno separately provided to us in order to facilitate a comparison between the holdings of Ancerno and 13F institutions. Second, we compare changes in quarterly holdings for all Ancerno institutions with changes in quarterly holdings for all 13F institutions. The results for both of these analyses are presented in Table A1. We find that the characteristics of stocks held and traded by Ancerno institutions, including size, book-to-market, lagged returns, volatility, and liquidity attributes, are not significantly different from the characteristics of stocks held and traded by the average 13F institution. Ancerno institutions primarily differ from the average 13F institution by institution size. Specific differences presented in Table A1 are discussed in Section 2.

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