Institutional Order Handling and Broker-Affiliated Trading Venues [*]

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Abstract

Using detailed order handling data over the life of 330 million institutional orders, we study whether order routing by brokers to Alternative Trading Systems (ATSs) that they own affects execution quality. In a multivariate regression specification that controls for stock attributes, order characteristics and market conditions, orders handled by brokers with high affiliated ATS routing are associated with lower fill rates. Trading costs based on the implementation shortfall approach are higher when clients select a broker with high affiliated ATS routing. Broker outcomes are highly persistent suggesting that improved disclosures on order handling could help institutional clients with broker selection.

Keywords: broker; intermediation; agency; venue; liquidity; trading; fund

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1. Introduction

Institutional investors account for a majority of ownership of US stocks, and serve as the primary vehicle for household investments. An important driver of institutional performance is the ability to implement investment ideas at a low cost. Trading costs subtract from institutional performance, erode or eliminate the value added by portfolio managers and lower the returns to research (Wagner (1993)). Anand, Irvine, Puckett and Venkataraman (2012) show that institutional trading costs are economically large and that broker selection is an important decision for managing trading costs.[1]

Brokers make a number of decisions on behalf of their clients. It is common for brokers to split an institutional order into smaller pieces, select among execution venues and sequence the submission of smaller orders across venues. To monitor and evaluate the quality of executions reported by brokers, institutional clients engage in transaction cost analysis. However, in recent years, industry participants and regulators have noted that the complexity of the US equity market structure makes it difficult for institutions to assess broker performance, especially since routing data is either unavailable or hard to decipher.[2]

Further, opaque reporting practices on the handling of institutional orders can obscure potential agency conflicts that influence broker routing decisions.[3] IOSCO (2017) discusses three potential sources of conflict in order routing: monetary incentives, such as venue fees; bundled

[1] Anand et al. (2012) estimate average institutional trading costs of 25 basis points over 1999 to 2008. ITG, Inc. reports average US equity execution costs of 23 basis points in Q2 2017 (https://www.itg.com/assets/ITG_Global-Cost-Review-2017Q2-Prelim-BrokerCostUpdated.pdf). Busse, Chordia, Jiang and Tang (2017) estimate that the trading costs accumulate to 0.75% per year for actively managed mutual funds.

[2] "Another substantial concern in the current market structure relates to the order routing practices of brokers, including the ability of large institutional customers to monitor those practices." SEC Chair Mary Jo White, keynote address, Securities Traders Association, September 14, 2016.

[3] According to Dan Royal, global head of trading at Janus Henderson, "Often we are left at the mercy of the analysis provided by the broker and as buy-siders we can be very skeptical of the data. Nobody will tell you if there is a conflict of interest..." The order routing enigma, *The Trade*, October 18, 2017.

services or soft dollars; and affiliated venues. Focusing on venue fees, Battalio, Corwin and Jennings (2016) show that broker routing of non-marketable retail order flow to trading venues that pay higher liquidity rebates is detrimental to the execution quality received by their clients. Brokers typically provide institutional clients with ancillary services, such as research and profitable IPO allocations. Conrad, Johnson and Wahal (2001) show that institutional orders routed to brokers with soft dollar arrangements are associated with higher trading costs.

In this study, we examine another largely unstudied, potential source of agency conflict – whether brokers' routing of orders to Alternative Trading Systems (ATSs) that they own affects execution quality. Specifically, we study three questions. Do brokers show a preference for routing client orders to affiliated ATSs? Is there any systematic association between routing preferences and execution quality? Finally, can order routing be explained by a preference for opaque ("dark") versus transparent ("lit") venues rather than affiliated versus unaffiliated venues?

Venue ownership can influence the broker's routing decisions in several ways. First, the brokerage firm receives trading fees on executions on its own venue instead of paying trading fees to other venues. Second, higher activity on the broker's venue is a mark of success, which is likely to attract other traders to the venue, thus further increasing trading fees. On the other hand, brokers have a duty of best execution to their customers, which generally requires brokers to seek executions that are as favorable as possible under prevailing market conditions. Vertical integration could potentially reduce costs, and clients could benefit to the extent that brokers share the cost savings with them. It is therefore unclear whether, and in which direction, broker routing to affiliated ATSs affects the execution quality of client orders.

To the best of our knowledge, there is no existing empirical evidence on the relation between venue ownership, broker routing and execution outcomes, which is likely due to lack of

suitable data.[4] In this study, we use the FINRA Order Audit Trail System (OATS) database that provides detailed information on institutional orders received by brokers. The broker-level parent orders (henceforth "top orders") include the identity of the broker handling an order; the venue-specific routing decisions; the venue-specific outcomes such as order executions and fill rates; and the execution price and the time stamps associated with each routing, modification, execution or cancellation decision in an order's lifecycle.[5] We examine over 330 million institutional top orders received by 43 active institutional brokers, consisting over 2.3 billion order events for a size-stratified sample of 273 stocks in October 2016.[6] The institutional order size is 1,371 shares, with the average share in the order routed approximately 10 times over the order's lifecycle.

Our results indicate that not all brokers that own an ATS show a preference to route client orders to affiliated ATSs. To identify a subset of brokers with a preference for affiliated ATSs, we estimate a sample-wide benchmark of the proportion of share quantity that is routed to affiliated ATSs on a stock-day. Brokers are placed in three groups (terciles) based on the broker's average deviations from the sample wide benchmark.[7] Brokers with the highest proportion of affiliated ATS routes are placed in the highest tercile (T3). For T3 brokers, routing to ATSs accounts for 64% of the routed quantity, which is largely attributable to affiliated ATS routes (50% of the routed quantity), while for brokers in lowest (T1) and middle (T2) terciles, ATSs accounts for 10% and

[4] There is anecdotal evidence that ATS ownership leads brokers to route client orders to affiliated venues. https://www.babelfishanalytics.com/news/2017/5/30/the-truth-behind-broker-routing-dont-believe-the-hype

[5] The data are similar to those underlying the statistics created by FINRA for the tick size pilot. More details are available at http://www.finra.org/industry/tick-size-pilot-program. The advantages of the OATS data in comparison to NYSE TAQ data and Abel-Noser institutional trading data are discussed in Section 3.

[6] We select the 30 largest stocks in each CRSP market cap decile. We obtain a final sample of 273 stocks after merging the initial sample with the filtered OATS data. We focus the analysis on the most active institutional brokers.

[7] Our sample of active institutional brokers includes those with no affiliated ATS. As expected, we observe a smaller proportion of brokers with affiliated-ATSs in tercile 1 than tercile 3.

25% of the routed quantity, respectively. The average share received by T3 brokers is routed 16.6 times, while the comparable statistic is 4.5 times for T1 brokers and 9.4 times for T2 brokers.

We study the relation between affiliated ATS routes and fill rates of orders. Fill rate over an order's "lifecycle" is the ratio of the filled shares to the total shares for a top order received by the broker. Filled shares for the top order are aggregated across all the child routes associated with the top order regardless of the number of child routes and the type of trading venue used to achieve the fills.[8] T3 brokers are associated with lower (17%) fill rates, while the comparable statistic for T1 (T2) brokers is 44% (30%). After controlling for stock attributes, order characteristics and market conditions in a regression framework, a one standard deviation increase in affiliated ATS routes is associated with an 11.6 percentage point decline in fill rates.

Are the lower fill rates for affiliated ATS routes offset by favorable transaction prices and smaller information leakage? We estimate trading costs based on the implementation shortfall approach, which accounts for fill rates, the bid ask spread, the market impact, and the drift in price during an order's lifecycle (see Perold (1988) and Wagner and Edwards (1993)). For an order that is fully executed, implementation shortfall is calculated by comparing the weighted average trade price with the prevailing NBBO quote midpoint at order arrival time. For orders with less than 100% fill rates, we impute an execution for unfilled portion of the order using either the closing price of the trading day, or the prevailing opposite NBBO quote (i.e., prevailing best quoted ask (bid) price for buys (sells)) at the time of the last observed event in the lifecycle. We also report effective spread costs, which compare the traded price of the filled portion of the order with order

[8] For this reason, the average fill rate in our sample is 30.3%, which is significantly higher than that reported using route level data, such as Tuttle (2013).

arrival price, thus ignoring the portion of the order that is unfilled.[9] These trading cost estimates accommodate different assumptions regarding the opportunity cost of non-execution borne by institutional clients.

Higher levels of affiliated ATS routes are associated with higher implementation shortfall costs. Even based on effective spreads, which ignores unfilled portion of an order, we do not find that trading costs are lower with high levels of affiliated ATS routes. For institutions that incur an opportunity cost for unfilled orders, our results suggest that trading costs are higher for brokers with high affiliated ATS routes. The differences in fill rates and implementation shortfall costs across broker terciles is highly persistent over time.

We recognize that a client's selection of a broker is an endogenous choice that could potentially impact our results. That is, institutions with a desire to access ATSs for less aggressive orders might select brokers with a preference for ATS routing. To study this explanation, we compare brokers with high affiliated ATS routes with other brokers with similar levels of ATS (but not affiliated ATS) routes. By holding the proportion of overall ATS routes across brokers the same, the analysis focuses on the role of affiliated versus unaffiliated ATS routes by a broker, thus isolating the impact of potential agency conflicts. After controlling for (intraday) market conditions and order characteristics, brokers with high affiliated ATS routes have fill rates that are 5.6 percentage points lower and implementation shortfall costs that are 1.13 to 1.95 basis points higher relative to matched brokers. These estimates translate to implementation shortfall costs that are 5.3% to 19.7% higher for brokers with high affiliated ATS routes.

[9] We follow the terminology in Perold (1998) in using "effective spread costs" to refer to the trading costs for the portion of the order that is filled. The implementation shortfall approach provides a trading cost estimate for both marketable and non-marketable top orders.

To further explore the role of broker selection, we adapt the paired route "horse race" approach developed by Battalio, Corwin, and Jennings (2016) to our empirical setting. We pair individual routes made by T3 brokers to affiliated ATSs with other identically priced, concurrent routes to unaffiliated ATSs. The pairs are midpoint peg orders (a commonly used order type that dynamically updates its limit price to the NBBO midpoint) that are open at the same time under similar conditions. Our results indicate that unaffiliated ATS routes have higher fill rates, and further, are more likely to obtain an earlier fill than the matched T3 broker-affiliated ATS routes. Although the two analyses that explores broker selection examine smaller samples than our main analysis, we do not find evidence that institutions' preferences for ATS venues explain our results.

Institutional investors face many challenges in measuring broker performance including opacity in order handling, the complex equity market structure and the ability to process high frequency data.[10] We show that broker routing patterns are highly persistent indicating that recent regulatory initiatives aimed at improving disclosure of routing practices would aid institutional clients with broker selection. We caution that ownership of a venue by itself does not constitute evidence of routing conflicts; indeed, not all brokers that own an ATS show a routing preference for their own venues. We also recognize that institutional clients could receive benefits from brokers that extend beyond execution services. In those cases, our study provides institutions with guidance on quantifying the tradeoffs involved in obtaining a portfolio of services from a broker.

[10] Institutional investors' concerns are the impetus behind the SEC's initiative to bring transparency to the handling of institutional order flow (See pages 11, 33-34, SEC (2016) "The Commission preliminarily believes that market-based efforts to provide institutional order handling transparency may not be sufficient insofar as smaller institutional customers may lack the bargaining power or the resources to demand relevant order handling information from their broker-dealers. In addition, while many institutional customers regularly conduct, directly or through a third-party vendor, transaction cost analysis ("TCA") of their orders to assess execution quality against various benchmarks, the Commission preliminarily believes that the comprehensiveness of such analysis could be enhanced with more granular order handling information". (https://www.sec.gov/rules/proposed/2016/34-78309.pdf)).

The rest of the paper is organized as follows. Section 2 presents the related literature while Section 3 describes data sources, sample selection and summary statistics. In section 4, we present the patterns of broker routing and its association with execution quality. Section 5 concludes.

2. Related literature

This study is related to the literature on brokers' routing of order flow pursuant to monetary benefits, such as preferencing arrangements or liquidity rebates. Easley, Kiefer and O'Hara (1996) provide evidence that payment for order flow arrangements siphon away uninformed order flow from public markets. Battalio (1997) and Battalio, Greene, Hatch and Jennings (2002) do not find that purchased order flow is associated with a deterioration in execution quality or quote competitiveness. Several recent studies examine whether order routing is influenced by make and take fees. Cardella, Hao and Kalcheva (2017) show that venue fees impact the market share of exchanges. Anand, Hua and McCormick (2016) and Battalio, Griffith and Van Ness (2016) find changes in order routing to options exchanges in response to fee changes. We add to these studies by studying whether broker ownership of venues impacts order routing and execution outcomes.

Our study adds to the literature that is motivated by the growth of market share of dark venues (Angel, Harris and Spatt (2015)). In describing the tradeoffs between dark and lit venues, Zhu (2014), Buti, Rindi and Werner (2017), and Menkveld, Yueshen and Zhu (2017) posit that exchanges offer the benefits of obtaining immediacy at a marked-up price while ATSs offer the opportunity to obtain better prices at a higher execution risk. Empirical studies of this tradeoff and its implications for order flow include Ye (2010), Tuttle (2013), Comerton-Forde and Putnins (2015) and Reed, Samadi, and Sokobin (2018), among others.

Given the trade-offs, a broker's decision to seek liquidity from an ATS venue, including an affiliated ATS, could represent an optimal strategy for a client order. While agency conflicts

are not considered in these studies, such conflicts raise the possibility that the broker selects affiliated ATSs under circumstances that differ from unaffiliated ATSs. Selecting an affiliated ATS when it is not optimal to do so could lead to missed trading opportunities on other venues and information leakage when suboptimal choice leads to order over-exposure.[11] For example, a conflicted broker may repeatedly route an order to affiliated ATS even when execution probability is low. In the presence of agency conflicts, holding the level of ATS routing the same, a broker's propensity to route orders to affiliated ATSs could lead to worse outcomes. Our results suggest that venue ownership is a relevant factor that influences the brokers' choice of trading venues.

Our study is related to the literature that examines how high frequency trading (HFT) affect institutional trading costs. Hendershott, Jones and Menkveld (2011), Brogaard, Hendershott and Riordan (2014), and Brogaard, Hagstromer, Norden and Riordan (2015) find that HFT are associated with improved market quality and price efficiency. Brogaard et al. (2017) find the HFT trade against extreme price movements. On the other hand, a recent literature links the market impact of institutional orders to HFT "back-runners" who detect order flow "footprints" and trade in the same direction as the institutional trader (see Yang and Zhu (2017) for theory and Kirilenko, Kyle, Samadi and Tuzun (2017), Van Kervel and Menkveld (2018), Saglam (2018), and Korajczyk and Murphy (2018) for empirical evidence). These studies point to a possible mechanism by which sub-optimal routing to affiliated ATS by a conflicted broker can cause higher price impact of institutional trades.

3. Data and sample description

3.1. Data sources and sample

[11] https://www.wsj.com/articles/a-suspect-emerges-in-stocktrade-hiccups-regulation-nms-1390881032?tesla=y

The primary dataset used in the study is the FINRA OATS database for the month of October 2016. Almost every broker-dealer in the U.S. is required to report audit trail information on equity orders to FINRA.[12] For each broker-level parent order ("top order") received from a client, OATS provides information detailing how the broker handled the top order. The dataset combines the identity of the broker handling the order, the beneficiary owner type, and the intended quantity of the broker-level order, with the audit trail of routes, venues, executions, modifications, and cancellations associated with the order's lifecycle.[13] These data are distinct from transaction level data such as the consolidated tape, or Trade and Quote (TAQ) data in providing a complete audit trail of broker level top orders. Our data are also distinct from institutional ticket data made available by Abel-Noser Solutions that were used by Puckett and Yan (2011) and Anand, Irvine, Puckett, and Venkataraman (2012, 2013). A limitation of the OATS data is that while it is possible to "stitch" together orders of an institution to a broker (i.e., top order) it is not possible to further stitch together top orders of an institution to several brokers. However, importantly for our analysis, when an institution sends a top order to a broker, OATS provides detailed information on broker routing, venue-level executions and fill rates, which are not available in Abel Noser data.

The sample of institutional brokers is based on the beneficiary owner classification from OATS, in combination with the institutional broker classification of Griffin, Harris, Shu, and Topaloglu (2011). The beneficiary owner field indicates whether an order represents institutional,

[12] Broker-dealers in the US are required to provide an audit trail to their primary Self Regulatory Organization (SRO). FINRA is the largest SRO responsible for the regulation of over 3,800 member firms in 2016.
[13] Werner (2003) uses an earlier iteration of OATS for an analysis of the impact of decimalization on institutional trading costs. Relative to the older data, we note some differences: the current version of OATS is linked to routes and executions in all venues; the number of orders is significantly larger; there are very few orders that are received as marketable orders; and fill rates are smaller.

individual, market maker, or proprietary interest.[14] To focus on active brokers, we require that brokers in our sample handle at least 10,000 institutional top orders in October 2016. Griffin et al. (2011), classify institutional brokers based on "company web pages, news media, the NASD website, and conversations with NASDAQ officials." Appendix A describes our selection of active, institutional brokers in detail.

As a validation check, our sample of 43 institutional brokers includes nine of the largest 10 brokers in a 2014 sample of institutional trading data from Abel-Noser Solutions. Since order splitting is common in recent data, it is challenging to use order size based definitions to identify institutional flow.[15] For this reason, our classification differs from studies using order size to identify institutional order flow (see Campbell, Ramadorai and Schwartz (2009) for a review of these studies). Using the FINRA broker reference file, which specifies the firm associated with each broker ID, we identify the brokers affiliated with firms that also own an ATS in the FINRA ATS transparency data.[16]

Our sample consists of a size-stratified group of 273 stocks traded in October 2016.[17] To construct the sample, we form decile portfolios using CRSP data on market capitalization at the end of September 2016 and select the 30 largest stocks from each decile. We merge the initial sample with the OATS database and TAQ National Best Bid and Offer (NBBO) quotes. We apply

[14] FINRA rule 4512 (c) defines institutions as a "bank, savings and loan association, insurance company or registered investment company; an investment adviser registered either with the SEC under Section 203 of the Investment Advisers Act or with a state securities commission (or any agency or office performing like functions); or any other person (whether a natural person, corporation, partnership, trust or otherwise) with total assets of at least $50 million". Agency orders that do not meet the criteria of the rule are classified as individuals.

[15] For example, comment letters from Bloomberg LP and Fidelity encourage the SEC to use the FINRA definition of institutions instead of a size-based cutoff to separate institutional and retail order flow. See https://www.sec.gov/comments/s7-14-16/s71416-15.pdf, and Fidelity letter at https://www.sec.gov/comments/s7-14-16/s71416-26.pdf.

[16] We examine direct ownership of an ATS where potential private benefits are largest. Consortiums of institutional participants own some ATSs. 26 of the 43 brokers in our sample are direct owners of an ATS.

[17] Our sample period overlaps with the implementation period of the tick-size pilot. We obtain qualitatively similar results when we restrict the sample to stocks unaffected by the tick-size pilot.

a number of filters (outlined in Appendix B) to obtain a final sample of 273 stocks. We classify stocks from the bottom three CRSP deciles as "small", the middle four deciles as "medium", and the top three deciles as "large" stocks. The final sample consists of over 330 million lifecycles of institutional top orders received by 43 institutional brokers. These orders are associated with over 2.3 billion events such as routes, executions and cancellations.

3.2. Measures of execution quality

The first measure of execution quality, the *fill rate* is the filled quantity divided by the submitted quantity of a top order. In the implementation shortfall approach, orders with fill rates below 100% incur an opportunity cost for unfilled portion of an order (see Perold (1988), Wagner and Edwards (1993)). We employ three approaches to measure opportunity costs that reasonably reflect the idiosyncratic preferences of institutional clients. *Effective spread cost* assumes that institutions incur no opportunity cost when an order is unfilled. Following Perold (1988) and Anand et. al. (2012), the measure for order lifecycle *i* received by broker *b* is calculated as follows:

$$\textit{Effective spread cost}_{(b,i)} = \frac{P_{1(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}, \tag{1}$$

where $P_{1(b,i)}$ is the share volume-weighted execution price, $P_{0(b,i)}$ is the NBBO bid-ask quote midpoint at the time when the broker receives the top order, and $D_{(b,i)}$ is a variable that equals 1 for buy orders and equals -1 for sell orders.

The next two measures impute an execution for the unfilled portion of an order. *Shortfall cross* follows Harris and Hasbrouck (1996) and Handa and Schwartz (1996) and assumes that traders cross the spread to trade at the opposite quote at the end of the life cycle:

$$\textit{Shortfall cross}_{(b,i)} = \left[f_{(b,i)} \times \frac{P_{1(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right] + \left[(1 - f_{(b,i)}) \times \frac{OQ_{(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right],$$

(2)

where $f_{(b,i)}$ is the *fill rate* and $OQ_{(b,i)}$ is the ask (bid) quote for buy (sell) orders at the time of the last event in the order's lifecycle. *Shortfall close* assumes that traders are able to fill the unfilled quantities in the daily closing auction. We define *shortfall close* as follows:

$$Shortfall\ close_{(b,i)} = \left[f_{(b,i)} \times \frac{P_{1(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right] + \left[(1 - f_{(b,i)}) \times \frac{Close_{(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right],$$

(3)

where $Close_{(b,i)}$ is the closing price obtained from CRSP. *Shortfall close* follows the approach in Keim and Madhavan (1997) and Conrad, Johnson and Wahal (2001), except that these studies use a closing price on subsequent days since the orders in their sample span several days.

We also calculate price movements *during* the lifecycle and *after* the end of the lifecycle. Institutions are concerned that sub-optimal broker routing practices lead to information leakage on the presence of the order. These concerns are particularly relevant since we observe the top order received by a broker and not the institutional ticket. An institution that splits a large ticket across brokers and trades over time is concerned about the impact of a broker's decisions on subsequent orders from the ticket. We calculate the price movements during the lifecycle *drift* as:

$$Drift_{(b,i)} = \frac{P_{T(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)},$$

(4)

where $P_{T(b,i)}$ denotes the quote midpoint at the time of the last observed event in the order's lifecycle. Finally, we define *post-drift* as:

$$Post\text{-}drift_{(b,i)} = \frac{P_{T+5(b,i)} - P_{T(b,i)}}{P_{T(b,i)}} \times D_{(b,i)},$$

(5)

where $P_{T+5(b,i)}$ denotes the quote midpoint five minutes after the last observed event in the order's life cycle. The price drift that is observed during and after the order cycle indicates whether broker routing allows the market to infer the presence of an institutional order. This measure is similar to price impact measure used in the literature (see Hasbrouck (2006)), except that price impact is conditional on observing a trade.

3.3. Descriptive Statistics

Table 1 describes the sample. Since we study the routing decisions of individual brokers, we aggregate statistics across top orders to the broker-stock-day level. The aggregation is a weighted average of the measures, where the weights are the share volume of the top order. Table 1 presents equally weighted averages of broker-stock-day observations. One notable difference between OATS relative to the TAQ data is that the size of the top order for our sample averages 1,371 shares, while the average reported trade size in the consolidated tape or TAQ is less than 200 shares.[18] Average order size in our sample of small stocks is 548 shares and that for large stocks is 1,915 shares. Average percentage quoted bid-ask spread at the time of order arrival is 37 basis points, and ranges from 7.6 basis points for large stocks to 102.5 basis points for small stocks. Given the large variation in liquidity across stocks, we present univariate results separately for small, medium and large stocks, and include stock fixed-effects in the multivariate regressions.

We observe a large number of routes associated with each order. An average share received by a broker is routed 10 times during an order's cycle. Since brokers are not allowed to represent trading intent greater than the order quantity, the statistic suggest that brokers sequentially route

[18] Angel, Harris and Spatt (2015) and O'Hara (2015) report an average trade size of 200 shares. Tuttle (2013) shows that 100 share trades account for approximately 70% of trades executed in exchanges and ATSs.

the orders to venues. Orders in small stocks are routed more often than for larger stocks, which points to the greater difficulty in executing trades in smaller stocks.

The average fill rate is 30.3%. Fill rates range from 22.7% for small stocks to 37.7% for large stocks, once again underlining the challenge in finding liquidity in small stocks. The fill rates documented here are substantially larger than fill rates seen at the venue level. This is because the OATS data allow calculation of fill rates for the top order, while venue data report fill rates of child orders routed to the venue.[19] Repeated exposure of the top order in the same or multiple venues leads to larger calculated fill rates in our analysis.

Effective spread costs are significantly smaller (2.5 basis points) than quoted spreads (37 basis points) at the time of order arrival, indicating that, on average, institutional orders do not aggressively seek liquidity. As expected, *shortfall close* yields smaller estimates of execution costs at 7 basis points, compared to 16.2 basis points for *shortfall cross*. Smaller stocks are more expensive to trade than larger stocks. On average, prices move adversely in the direction of the order. The average *drift* is 3.4 basis points and the average *post-drift* is 0.7 basis points, with large drifts observed for smaller stocks. While the natural interpretation is that *post-drift* is a measure of information leakage, an alternate interpretation is that *post-drift* is a measure of market conditions. In some regression specifications, we use *post-drift* as an additional measure of market conditions to account for possible differences in order difficulty across brokers.

2.3. Venue choice statistics

Table 2 describes the average routing of our sample of brokers to three broad categories of venues – ATSs, exchanges and firms. "Firms" refers to brokers that act as execution venues; for

[19] For example, if a hypothetical order for 1,000 shares gets routed 100 times to execute 700 shares, the fill rate is 70% even though the majority of the routes are associated with non-execution or cancelation. Tuttle (2013) finds ATS fill rates close to 1%. As a point of comparison, we find fill rates of 3.30% at the route level. We note that our sample is limited to institutional order flow.

example, large wholesalers that purchase order flow fall in this category. Table 2 shows that, across all stocks, the proportion of executions in a venue type is strikingly different from the proportion of routes. Although exchanges receive only 58.8% (54.8%) of the routes (routed quantity), they account for 77.8% (73.8%) of executions (executed quantity). In contrast, ATSs receive 29.5% (32.5%) of the routes (routed quantity) but account for only 13.4% (16.7%) of executions (executed quantity). We observe similar patterns across all stock categories.

To describe the broker's pecking-order of venue types for institutional orders, we calculate a rank measure for ATSs and Exchanges, respectively, using top order with multiple routes. If the average time-to-route is shorter on ATSs relative to exchanges, we assign a rank of 1 to ATSs and a rank of 2 to exchanges (and vice-versa). If it is a tie, we assign a rank of 1.5 to both venue types. The volume-weighted average ranks in Panel E suggest that brokers prefer to route orders to ATSs before routing the order to exchanges, consistent with Menkveld, Yueshen, and Zhu (2017).

4. Results

4.1 Affiliated ATS routing

Table 3 examines brokers' propensity to route orders to affiliated ATSs. For each broker-stock-day, we calculate the proportion of routed quantity directed by the broker to its affiliated ATS. The benchmark for each stock-day is the proportion of total routed quantity directed to affiliated ATSs across all brokers. We divide the brokers into terciles based on their average deviation from the stock-day benchmark over the sample. Tercile 1 (T1) brokers route to affiliated ATSs less than the benchmark on average, while tercile 3 (T3) brokers route to affiliated ATSs more than the benchmark on average. Table 3 presents averages of the broker-stock day observations. This analysis allows for different outcomes associated with relative overweighting and underweighting of routing to affiliated ATSs.

Results in Table 3 indicate large differences in routing behavior across brokers. T1 and T2 brokers route 10.2% and 25.3% of shares to ATSs, respectively. T1 brokers do not route to affiliated ATSs, while T2 brokers route 6.5% of shares to affiliated ATSs.[20] In the case of T1 and T2 brokers, 70.8% and 62.3% of shares are routed to exchanges.[21] Approximately 77% (74.5%) of executed quantity for T1 (T2) brokers occurs on exchanges.

T3 brokers differ markedly from the other two groups with 49.9% of their routed quantity sent to affiliated ATSs, and all ATSs accounting for 63.6% of routed quantity. Furthermore, T3 brokers show a large difference between the proportion of routed quantity (49.9%) and execution quantity (16.8%) occurring on affiliated ATSs. The majority of T3 brokers' executions occur on exchanges. Notably, exchanges account for only 30.1% of T3 brokers' routed quantity but 70% of executed quantity. The differences between the routing preferences of T3 brokers versus the other groups are statistically significant in the full sample and across small, medium and large stocks.

To examine the intertemporal characteristics of these brokers' preferences, we compute the average sequence rank measure for each broker tercile. Table 3 shows that T1 brokers show no preference for routing to ATSs or exchanges, with a rank of 1.51 for ATSs and 1.50 for exchanges. Both T2 and T3 brokers are more likely to route to ATSs first, but the preference is stronger for T3 brokers. The average ATS rank for T2 brokers (1.43) is statistically larger than that of T3 brokers (1.39).

In Panel B, we examine whether the ranking of institutional brokers based on affiliated ATS routing is persistent. We classify brokers into terciles based on average stock-day deviations of affiliated ATS routing from the sample-wide benchmark during the first week of October 2016

[20] Tercile 1 includes some brokers without any affiliated ATSs. Only 32% of T1 brokers are affiliated with an ATS compared to 83% of T2 brokers and 100% of T3 brokers.
[21] Apart from exchanges and ATSs, brokers also route to other brokerage firms or internalize orders. These are included as "firm" routes in Table 2.

and then report affiliate routing statistics for the three remaining weeks in the month. We also report the retention rate, which is the percentage of brokers who continue to be classified in the same tercile in future weeks. The patterns indicate that broker ranking is highly persistent. In all future weeks, the affiliated ATS routing statistic increases from tercile 1 to tercile 3 and the retention percentage exceeds 80 percent indicating that brokers' routing behavior stays consistent over time. Thus, institutional investors can select brokers based on their past experience with brokers.

4.2 Execution Quality: Univariate Statistics

Anand et. al. (2012) find evidence that trading costs are lower for skilled brokers and that low cost brokers outperform high cost brokers in a persistent manner. We extend the analysis by examining whether routing practices can be an explanation for the trading cost differential across brokers. Table 4.A. presents average execution outcomes for broker terciles based on affiliated ATS routing. The average *fill rate* of orders handled by T3 brokers is significantly smaller than that for orders handled by T1 or T2 brokers. For the average order, 43.5% of order quantity is filled for T1 brokers, 29.8% for T2 brokers and only 16.9% for T3 brokers.

The lower execution probabilities at ATS venues is well known; however, as noted earlier, a strategy where a T3 broker initially selects an affiliated ATS but subsequently selects exchanges would improve fill rates for a top order. Since our analysis measures fill rates for the top order, it is noteworthy that T3 brokers deliver lower fills despite their ability to route to venues with higher execution probabilities. The differences in fill rates are not simply an artifact of brokers receiving orders in different stocks, as similar patterns exist for small, medium and large stocks.

Trading costs based on the *effective spread cost* measure assume that traders are indifferent to non-execution and simply abandon the unfilled part of the order with no associated opportunity

costs. In the overall sample, the *effective spread costs* of T3 brokers are 3.2 bps, followed by 3.1 bps for T2 brokers and 1.1 bps for T1 brokers. T3 brokers have higher costs than T1 brokers for medium and large stocks while the differences are not statistically significant for small stocks.

Shortfall close, which assumes that the unfilled part of the order executes at the closing price, is larger for T3 brokers at 10.7 bps than for T1 (3.2 bps) or T2 (7.5 bps) brokers. T3 brokers have statistically significantly larger *shortfall close* relative to T1 and T2 brokers for the overall sample and for small, medium and large stocks. The results are broadly similar for *shortfall cross*, which assumes that the unfilled part of the order is executed at the opposite quoted price at the end of the lifecycle. The average *shortfall cross* for T3 brokers is approximately 20.5 basis points, which is significantly larger than the 10 bps for T1 brokers and 18.4 bps for T2 brokers.

Notably, adverse price movements, as captured by *post-drift,* are significantly larger for T3 brokers relative to T1 and T2 brokers for the overall sample, as well as sub-samples based on market capitalization. The larger *post-drift* points to the possibility that the routing decisions of T3 brokers are associated with greater information leakage about the order. Price movements during the lifecycle, as captured by *drift*, do not show consistent differences across broker terciles.

Another possibility is that institutions use T3 brokers when market conditions are difficult to execute an order. We report the percentage quoted spreads prevailing at the time a broker receives a top order. For the overall sample, arrival spreads are 44 bps for T3 brokers, 40 bps for T2 brokers and 27 bps for T1 brokers. However, results in Panels B to D indicate that patterns are quite different across market capitalization groupings. For large stocks, arrival spreads for T3 brokers are in fact statistically lower than other groups; for medium stocks, the differences are not statistically significant, and for small stocks, arrival spreads of T3 brokers are larger than other

groups. These patterns suggest that it is important to control for order difficulty and market conditions.

4.3 Multivariate analysis of execution costs

Table 5 examines the relation between ATS executions and execution quality based on multivariate regression specifications where control variables account for stock characteristics, order attributes and market conditions. We estimate the following regression models:

$$Y_{i,s,t} = \beta_1 \%Affiliated\ ATS_{i,s,t} + \beta' \mathbf{X} + FE + \epsilon_{i,s,t}, \quad (6)$$

where $Y_{i,s,t}$ is the execution outcome for broker *i* in stock *s* on day *t*. Outcomes include: *fill rates*, *effective spread costs*, *shortfall close*, *shortfall cross, drift* and *post-drift*. The variable of interest, %*Affiliated ATS*, is a continuous measure of the proportion of routed quantity to affiliated ATSs. **X** is a vector of control variables: log of average order size on the broker-stock-day, the average arrival percentage quoted spread on the broker-stock-day and stock controls including the log of the stock price, log of the market capitalization and the sum of squared five-minute mid-quote log returns (realized volatility) for each stock-day. Order size accounts for the well-known result that order difficulty increases with order size. Arrival-time spreads account for variations in market liquidity over time. Stock attributes, such as price, market cap and volatility account for differences in the difficulty to execute orders across stocks. In specifications (3) and (4), we use stock fixed effects instead of stock characteristics. In specifications (2) and (4), we include the average *post-drift* on the broker-stock-day as an additional measure of market conditions. As discussed earlier, to the extent that broker decisions leads to information leakage, this approach is conservative as it is reasonable to classify *post-drift* as an outcome of broker decisions. Test statistics are based on standard errors that are clustered by stock and day.

Models 1 to 4 in Table 5 report different specifications with the *fill rate* as the dependent variable. The point estimates for *%Affiliated ATS* indicate that brokers with higher affiliated ATSs routes obtain lower fill rates, after controlling for differences in stock attributes, order characteristics and market conditions. In all specifications, *%Affiliated ATS* is highly significant at the 1% level. The most conservative estimate (model 4), suggests that a one standard deviation increase in *%Affiliated ATS* is associated with an 11.6 percentage point decline in fill rates. The economic impact of routing orders to affiliated ATSs is substantial as the average fill rate for our sample is 30.3%. Other control variables are of the expected sign. Fill rates are positively associated with market cap and negatively associated with larger arrival spreads.

With the *effective spread cost* as the dependent variable, Table 5 shows that the coefficient on *%Affiliated ATS* is statistically insignificant in all specifications. Theoretical models on lit versus dark venues point to lower trade execution costs as the important benefit of ATS venues. Notably, the evidence does not support that institutions benefit in the form of lower trading costs from using affiliated ATSs, even based on a trading cost measure that imposes no penalty on the unfilled portion of an order.

The results indicate that affiliated ATS routing is associated with larger implementation shortfall as measured by both *shortfall close* and *shortfall cross*. Table 5 shows that the coefficients for *shortfall close* are significant at the 1% level in all four models. We note that the inclusion of stock fixed effects and *post-drift* presents a stringent robustness test for these results. Taking the most conservative estimate, the results suggest that a one standard deviation increase in *%Affiliated ATS* is associated with a 1.7 basis points larger *shortfall close* for the broker. We note that this translates to 24.1% of the unconditional average *shortfall close* in the sample.

Table 5 also shows that *shortfall cross* is significantly larger for brokers with higher affiliated ATSs routes. The arrival spread is significant in these models, since *shortfall cross* assumes that the unfilled portion of the order is executed by crossing the spread at the end of the order lifecycle, and arrival spreads are likely to be correlated with end of lifecycle spreads. *Shortfall cross* is consistent with prior literature but imposes a large cost for unfilled orders. At the same time, the measure assumes that the entire order can be filled at the opposite quote; that is, orders do not "walk the book" in this measure. In economic terms, the most conservative estimate suggests that a one standard deviation increase in *%Affiliated ATS* is associated with a 0.9 basis point larger *shortfall cross* for the broker, which translates to 5.7% of the unconditional average.

Is affiliated ATS routing associated with lower information leakage? We examine the price drift measures (*drift* and *post-drift*) in a regression framework in Table 5. We find that the *drift* is decreasing in *%Affiliated ATS* while *post-drift* increases in *%Affiliated ATS*. Notably, while information leakage is lower with higher Affiliated ATS routes on a relative basis, the *drift* is positive, as shown in Table 4, and in aggregate, the large unfilled portion of the Affiliated ATS routes is exposed to the adverse price movements during the lifecycle of the order, leading to higher opportunity costs. Further, the larger *post-drift* for affiliated ATS routes suggests that clients who desire full executions are likely to incur higher costs for the unfilled portion of the order.

4.4 Persistence in execution outcomes

In Table 6, we examine whether the relationship between affiliated ATS routing and the outcomes on execution quality are persistent. We classify brokers into terciles based on affiliated ATS routing on day *t*, and then follow the trends in execution outcomes from days *t* through *t+4*. The unit of observation is the broker-stock-day that is then averaged up to the broker-day level by taking an equally-weighted average across stocks. Day *t* results simply repeat prior analyses and

hence yield similar inferences, the *fill rate* for T3 brokers is significantly smaller than T1 brokers; and both, *shortfall close* and *shortfall cross* are significantly larger. Notably, the measures are remarkably persistent with almost no material change in magnitudes over the future days *t+1* through *t+4*. The persistence indicates that as the brokers' routing behavior stays consistent over time, so do the outcomes associated with their routing. In the absence of transparency on brokers' routing practices, one important implication of this analysis is that institutional investors can select brokers based on their prior experience with brokers.

4.5 Matched analysis

There is a possibility that orders routed to high-affiliated ATS routing (T3) brokers are different from other orders in ways not entirely captured by control variables. In this section, we examine the possibility that clients select a T3 broker with the intention of seeking liquidity on ATSs. Using nearest neighbor one-to-one propensity scores, we match a T3 broker on a stock-day with a T1 or T2 broker on the same stock-day with similar proportion of share quantity routed to ATSs. Thus, the overall routing to ATSs for treatment and control groups is similar but the treatment group (T3) brokers have a significantly higher proportion routed to affiliated ATSs in comparison to the control group.

We note that the matched analysis is limited as compared to the unconditional analysis in Table 5. If T1 or T2 brokers route a significantly lower proportion to ATSs than T3 brokers on a stock-day because market conditions don't favor such routing, the matched analysis will fail to capture the impact of those decisions and is likely to understate the differences between affiliated and unaffiliated routing. However, the analysis adds useful robustness by helping control for client's desire for ATS execution and isolates the impact of agency conflicts.

Since brokers are matched at the stock-day level, stock characteristics and daily market conditions are exact matches. Using a caliper of one quarter of a standard deviation, we are able to obtain a well-matched sample based on overall ATS routing. For the 38,548 matched broker-stock-days in the sample, the average proportion of routed quantity to ATSs for the treatment group is 51.2% and for the control group is 50.1%. By construction, the two groups differ on affiliated ATS routing. Affiliated ATS routing accounts for 41.5% of routed quantity for the treatment group but only 7.2% for the control group. We estimate the following specification to examine differences in execution outcomes for T3 brokers relative to matched brokers:

$$Y_{i,s,t} = \beta_1 T3_{i,s,t} + \beta' \boldsymbol{X} + FE + \varepsilon_{i,s,t} \quad (7)$$

where $Y_{i,s,t}$ is the execution outcome for broker *i* in stock *s* on day *t*. $T3_{i,s,t}$ equals one for T3 brokers and zero for control brokers. The vector of control variables, **X** is limited to those that vary within a stock-day and include log of the average order size on the broker-stock-day, the average arrival-time percentage quoted spread on the broker-stock-day; and, the *post-drift*. Importantly, the specification includes matched-pair fixed effects, allowing $T3_{i,s,t}$ to capture paired differences. Test statistics are based on standard errors clustered by stock and day.

Table 7 presents the results. *Fill rates* for T3 brokers are significantly lower (5.6 percentage points) than for matched brokers. While *effective spread costs* are 1.29 basis points lower for T3 brokers, with estimates statistically significant at the 10% level, T3 brokers' *shortfall close* and *shortfall cross* are significantly larger. In the most conservative estimates, *shortfall close* is 1.95 basis points larger for T3 brokers (significant at the 5% level), and *shortfall cross* is 1.13 basis points larger (significant at the 10% level). These *shortfall close* and *shortfall cross* estimates correspond to incremental costs of 19.7% and 5.3% relative to their respective unconditional

means in the matched sample. Differences in *post-drift* are statistically indistinguishable from zero, though *drift* is also significantly larger for T3 brokers. Thus, controlling for client's preference for ATS routing, T3 brokers have higher trading costs when opportunity costs of non-execution are included. The evidence does not support the argument that T3 brokers better manage information leakage and adverse price movements relative to matched brokers with similar ATS usage.

4.6 Matched order horse races

To further control for the role of broker selection, we adapt the paired route "horse race" approach developed by Battalio, Corwin, and Jennings (2016) to our empirical setting. We pair individual routes made by T3 brokers to affiliated ATSs with other identically priced, concurrent routes to unaffiliated ATSs. The pairs are midpoint peg orders, which are a commonly used order type at ATSs during our sample period. These orders have a dynamically updating limit price set equal to the midpoint of the prevailing NBBO. We further require the matched orders to be open at the same time, and to be submitted under similar market conditions. [22] Similar to Battalio et al. (2016), we require that at least one of the matched orders receives a partial or complete fill. Specifically, the first order in the order pair must be active, unmodified, and not have received a fill when the second order in the pair is routed. To consider orders that are submitted under similar market conditions, we further require that the matched pegged orders arrive during the same NBBO price. Following Battalio et al. (2016), if both orders obtain an execution within 500 milliseconds of one another, the horse race is declared a tie.

Table 8 describes the 1,421,432 matched pairs. The average fill rate, calculated as the executed quantity of the child order divided by the order quantity of the child order, in the sample

[22] Traders often use ATSs to obtain midpoint executions. We focus on midpoint peg orders as they are commonly used at the ATSs in our sample.

of T3 broker affiliated ATS routes is 41.1%, which is significantly lower than 50% fill rate for the matched unaffiliated ATS routes. We also find that unaffiliated ATS routes obtain fills more quickly than T3 broker affiliated ATS routes. Specifically, unaffiliated ATS routes receive a fill first 53% of the time, T3 affiliated ATS routes receive a fill first 42% of the time, and the horse race is a tie approximately 5% of the time. Similar patterns are observed when analysis is run on subsamples of large, medium and small stocks. Overall, the results of the horse race analysis of matched orders supports the main results that routes to unaffiliated ATSs outperform those to T3 affiliated ATSs.[23]

5. Conclusion

Institutional brokers play an important role in the trade execution process of institutional investors. In the absence of agency conflicts, brokers make routing decisions that obtain the best possible execution outcomes for clients under prevailing market conditions. In an important work, Battalio, Corwin and Jennings (2016) show that financial incentives, such as rebates and fees, influence the broker's choice of routing venue, and such incentives hurt the execution quality of retail clients. In this study, we examine whether another potential source of agency conflict - broker usage of Alternative Trading Systems (ATS) that they own - affects the execution quality of institutional client orders. We examine FINRA's Order Audit Trail System (OATS) data, which provides detailed routing information over the lifecycle of an institutional order.

We identify institutional brokers that exhibit a preference for routing orders to affiliated ATSs. Brokers with high-affiliated ATS routing are associated with lower fill rates over the entire lifecycle of the order. Trading costs based on the implementation shortfall approach reflect a

[23] Unlike Battalio, Corwin and Jennings (2016), we do not include good fill ratios in our analysis. The ratios are calculated using price movements after the execution of a route. In our analysis, the orders are pegged to a moving NBBO which makes the measure less useful than when the limit price is fixed.

number of potential scenarios on the opportunity costs of non-execution. In our analysis, to isolate the impact of brokers' affiliated ATS usage on execution quality, we control for stock attributes, order attributes and market conditions in a regression framework. For institutional clients that bear an opportunity cost for unfilled orders, trading costs are higher when the order is handled by a broker with high affiliated ATS routes. Further analyses do not support the argument that institutions' preferences for ATS venues explain our results. Our study provides empirical support for recent regulatory initiatives that attempt to improve the disclosure of potential broker conflicts and increase transparency on handling of institutional order flow.

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Appendix A

Identifying institutional brokers and order flow

Our focus in this study is on institutional order flow handled by institutional brokers. We use a combination of the broker classifications from Griffin et al. (2011) and the beneficiary owner field in the OATS data for our identification. The beneficiary owner field in the data can indicate institutional, individual, combined, employee, market maker or proprietary flow. There are also cases where the beneficiary owner type is marked as unknown or is null in the data. In the identification methodology described below, we implicitly assume that brokers are unlikely to mark their own (proprietary or market making flow) as unknown. Thus, the choice of whether to include choice of orders with unknown beneficiary owner type rests on the likelihood of these orders being from institutional or individual clients.

The Griffin et al. (2011) institutional brokers serve as our starting point:

1. If Griffin et al. (2011) identify a broker as "Institutional" or "Largest Ibanks", then we examine all of the broker's orders except those marked as non-institutional. That is, we include orders marked as institutional or unknown, and exclude orders marked as individual, proprietary or market making. The overlay of beneficiary owner type on the Griffin et al. (2011) classification allows for the possibility that institutional brokers may handle some other types of order flow as well.
2. If Griffin et al (2011) classify the broker as "Mixed", at least 40% of the orders have a known beneficiary type and at least 60% of the orders with a known type are marked as institutional, then we examine all of the broker's orders except those marked as non-institutional.

3. If Griffin et al (2011) classify the broker as "Mixed" and less than 40% of the orders have a known beneficiary type, then we only examine those orders that are marked as institutional. The difference from criteria (1) and (2) above is in the treatment of orders with unknown beneficiary type. For "mixed" brokers with a large proportion of unknown beneficiary orders, we are less confident that unknown beneficiary orders are likely to be institutional.
4. If Griffin et al (2011) do not classify a broker, we classify the broker based on the OATS data alone. For a broker to be identified as institutional, we require that at least 40% of the orders have a known beneficiary type and at least 40% of the orders with a known type are marked as institutional. As in (3) above, for these brokers, we only include orders marked as institutional.
5. To ensure that we focus on active brokers, we require at least 10,000 top orders received by the broker that survive the filters imposed above.
6. Finally, we exclude brokers that are primarily associated with internalized flow, or are likely to serve as conduits to ATSs. Specifically, we remove brokers who execute more than 60% of their executed quantity with non-ATS brokers, brokers who route 100% of their order flow to affiliated ATSs, brokers who receive the majority of their routed order flow from other brokers, and well known proprietary firms and market makers.

Appendix B

Data Filters

We impose several data filters:

- We remove orders received outside of trading hours.
- We remove orders with more than one top order assigned to the lifecycle. This would be the case if top orders are merged by the broker before routing. This merge makes our attribution of order handling more difficult.
- We remove stocks with a share price less than $1.
- We remove orders that were received but are not associated with any routes by the broker.
- We remove orders with lifecycle events that span multiple days.
- We remove orders with a fill rate greater than a 100%, and shortfall costs that are greater than 10% or lower than -10%.
- We remove orders whose time-to-execution or time-to-route was less than -2 seconds due to clock synchronization issues.

To construct NBBO quotes, we consider nbbo quotes from the TAQ NBBO and Quote files whose quote conditions are not equal to 'A','B','H','O','R','W', remove cancelled quotes, remove quotes without an associated positive share quantity or price. We remove quotes corresponding to locked and crossed markets and percentage bid-ask spreads larger than 10%.

For horse races, we remove ATS child orders with more than one "new order" event and child orders with a fill rate greater than a 100%. We use the order handling codes "FM" and "PEG" to identify midpoint pegged orders. We verify that at least 70% of executions for the order handling codes for each broker used in the horse races take place at the midpoint of the NBBO.

Table 1: Descriptive statistics

This table presents descriptive statistics for the sample. For each measure, broker-stock-day observations are constructed by taking top order quantity weighted averages of top orders received by a broker on a stock-day. The tables presents equally weighted averages of the broker-stock-day observations. Statistics are presented for the overall sample and for small (smallest 30%), medium (middle 40%), and large (largest 30%) market capitalization stocks. *Order size* is the average order size. *Rt qty/order qty* is the ratio of number of shares routed during the orders lifecycle to its top order quantity. *Fill rate* is the ratio of executed quantity to top order quantity. *Arrival spread* is the percentage quoted NBBO spread at the time an order arrives at a broker. *Effective spread cost* represents the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker. *Shortfall close* measures the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. The costs for the executed portion of the order is measured as in effective spread costs. *Shortfall cross* measures the implementation shortfall by imputing a fill at the opposing NBBO quote at the end of the order for the unexecuted portion of the order. *Drift* is the average signed NBBO midquote percentage return over the life of an order. The life of an order is measured from order arrival to the last observed event in the orders lifecycle. *Post-drift* is the average signed NBBO midquote percentage return over the five minutes after the end of an order lifecycle.

	#Brokers	#Obs	#Orders (mm)	Order size	Rt qty/ order qty	Fill rate
All stocks	43	139265	331.20	1371.18	10.05	30.33%
Large stocks	43	54210	245.23	1915.08	5.61	37.68%
Medium stocks	43	57382	72.03	1254.32	9.04	27.06%
Small stocks	40	27673	13.93	548.00	20.83	22.69%

	Arrival spread (bp)	Eff. spread cost (bp)	Shortfall close (bp)	Shortfall cross (bp)	Drift (bp)	Post-drift (bp)
All stocks	36.77	2.49	7.04	16.18	3.36	0.71
Large stocks	7.55	1.23	2.99	3.70	1.55	0.06
Medium stocks	32.68	2.20	6.57	14.47	3.55	0.74
Small stocks	102.48	6.21	15.95	44.19	6.50	1.92

Table 2: Venue choice statistics

This table presents routing and execution venue choice statistics. The proportions presented are equally weighted averages of broker-stock-day observations. Statistics are presented for the overall sample and for small (smallest 30%), medium (middle 40%), and large (largest 30%) market capitalization stocks. Panel A presents the proportion of routes to different venue types, Panel B presents the proportion of executions by venue type, Panel C presents the proportion of routed share quantity by venue type, and Panel D presents the proportion of executed share quantity by venue type. Panel E presents average venue route sequence ranks. For a given order lifecycle with at least one route each to an ATS and an exchange, volume weighted average time-to-route (in seconds) is calculated for ATSs and exchanges. A rank of 1 is assigned to the venue type with the shorter time-to-route and a rank of 2 is assigned to the other venue type. A rank of 1.5 is assigned to both venue types in the event of a tie. The percentage of lifecycles with both ATS and exchange routes, for which sequence rank measures are computed, is also presented.

	Panel A: Routes			*Panel B: Executions*		
	ATS	Exchange	Firm	ATS	Exchange	Firm
All orders	29.52%	58.81%	11.67%	13.42%	77.77%	8.82%
Large stocks	26.63%	58.78%	14.58%	12.80%	76.47%	10.72%
Medium stocks	30.51%	58.82%	10.67%	14.41%	77.57%	8.02%
Small stocks	33.13%	58.85%	8.02%	12.50%	81.36%	6.15%

	Panel C: Routed qty			*Panel D: Executed qty*		
	ATS	Exchange	Firm	ATS	Exchange	Firm
All orders	32.50%	54.81%	12.69%	16.70%	73.82%	9.48%
Large stocks	30.60%	53.35%	16.05%	16.69%	71.85%	11.46%
Medium stocks	33.23%	55.23%	11.55%	17.59%	73.82%	8.59%
Small stocks	34.73%	56.78%	8.48%	14.56%	78.57%	6.87%

	Panel E: Route sequence rank		
	ATS	Exchange	%Orders
All orders	1.43	1.58	18.99%
Large stocks	1.42	1.58	19.06%
Medium stocks	1.44	1.57	18.50%
Small stocks	1.42	1.58	20.25%

Table 3: ATS affiliation and venue choice

This table describes venue choice and routing characteristics by broker preference for routing to affiliated ATSs. In Panel A, brokers are grouped into terciles based on a broker's average deviation from a stock-day sample-wide affiliated ATSs routed quantity benchmark. Units of observation are broker-stock-day proportions. *Rt qty/order qty* ratio of number of shares routed during the orders lifecycle to its top order quantity. *Order size* is the average order size. Average routed share quantity proportions (*rt qty*) and executed share quantity proportions (*ex qty*) are calculated for *ATSs*, *affiliated ATSs*, *unaffiliated ATSs*, *exchanges*, and *firms* separately. Average venue sequence ranks are also presented. For a given order lifecycle with at least one route each to an ATS and an exchange, volume weighted average time-to-route in seconds are calculated for ATSs and Exchanges. A rank of 1 is assigned to the venue type with the shorter time-to-route and a rank of 2 is assigned to the other venue type. A rank of 1.5 is assigned to both venue types in the event of a tie. In Panel B, brokers are sorted into terciles based on their average deviation from a stock-day sample-wide affiliated ATSs routed quantity benchmark during the first week of the sample. Holding this tercile rank constant, brokers average routed share quantity proportion to affiliated ATSs is examined over each of the following three weeks. *Retention %* is the percentage of brokers that remain in the same tercile in the future week.

Panel A: Venue choice statistics by broker tercile

		Rt qty/	Order	%ATS		%Affiliated ATS		%Unaffiliated ATS	
Broker tercile	#Obs	order qty	size	Rt qty	Ex qty	Rt qty	Ex qty	Rt qty	Ex qty
T1 (least %affiliated ATS)	47841	4.53	2183.95	10.16	5.96	0.00	0.00	10.16	5.96
T2	46408	9.41	1250.60	25.33	16.40	6.46	4.81	18.88	11.60
T3 (most %affiliated ATS)	45016	16.56	631.71	63.64	27.37	49.87	16.78	13.76	10.59
T1-T3			1552.24***	−53.47***	−21.41***	−49.87***	−16.78***	−3.60***	−4.63***
T2-T3			618.89***	−38.30***	−10.96***	−43.42***	−11.97***	5.12***	1.01***

	%Exchange		%Firm		Route sequence rank	
Broker tercile	Rt qty	Ex qty	Rt qty	Ex qty	ATS	Exchange
T1 (least %affiliated ATS)	70.81	77.00	19.03	17.04	1.51	1.50
T2	62.28	74.53	12.38	9.06	1.43	1.57
T3 (most %affiliated ATS)	30.10	70.01	6.27	2.62	1.39	1.62
T1-T3	40.71***	6.99***	12.76***	14.42***	0.12***	−0.12***
T2-T3	32.19***	4.52***	6.12***	6.44***	0.04***	−0.04***

Panel B: Persistence in Venue Choice

	Week			
Broker Tercile	Week T	Week $T+1$	Week $T+2$	Week $T+3$
Tercile 1 (least %affiliated ATS)	0.00	0.00	0.00	0.00
Retention %	100.00	90.91	97.16	95.17
Tercile 2	5.86	6.04	7.05	6.93
Retention %	100.00	80.20	90.31	95.37
Tercile 3 (most %affiliated ATS)	50.05	51.49	49.71	48.60
Retention %	100.00	83.15	88.15	100.00
T3-T1	50.05	51.49	49.71	48.60
T3-T2	44.20	45.46	42.66	41.67

*p<0.1; **p<0.05; ***p<0.01

Table 4: ATS affiliation and execution quality, univariate analysis

This table presents univariate statistics examining the relation between ATS affiliation and execution quality. Brokers are grouped into terciles based on their average deviation from a stock-day sample-wide benchmark of the proportion of routed share quantity to affiliated ATSs. Units of observation are broker-stock-day top order quantity weighted averages. *Fill rate* is the ratio of executed quantity to top order quantity. *Arrival spread* is the percentage quoted NBBO spread at the time an order arrives at a broker. *Effective spread cost* represents the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker. *Shortfall close* measures the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. The costs for the executed portion of the order is measured as in effective spread costs. *Shortfall cross* measures the implementation shortfall by imputing a fill at the opposing NBBO quote at the end of the order for the unexecuted portion of the order. *Drift* is the average signed NBBO midquote percentage return over the life of an order. The life of an order is measured from order arrival to the last observed event in the orders lifecycle. *Post-drift* is the average signed NBBO midquote percentage return over the five minutes after the end of an order lifecycle.

Panel A: All stocks

Broker tercile	#Obs	Fill rate	Arrival spread (bp)	Eff. spread cost (bp)	Shortfall close (bp)	Shortfall cross (bp)	Drift (bp)	Post-drift (bp)
T1 (least %affiliated ATS)	47841	43.50%	26.93	1.10	3.15	9.97	2.74	−0.57
T2	46408	29.79%	39.94	3.13	7.49	18.39	3.76	0.75
T3 (most %affiliated ATS)	45016	16.87%	43.95	3.17	10.69	20.51	3.59	2.04
T1-T3		26.63%***	−17.02***	−2.07***	−7.54***	−10.54***	−0.85***	−2.61***
T2-T3		12.92%***	−4.01***	−0.04	−3.20***	−2.12***	0.17	−1.29***

Panel B: Large stocks

Broker tercile	#Obs	Fill rate	Arrival spread (bp)	Eff. spread cost (bp)	Shortfall close (bp)	Shortfall cross (bp)	Drift (bp)	Post-drift (bp)
T1 (least %affiliated ATS)	23642	47.54%	8.68	0.42	1.64	3.37	1.26	−0.24
T2	15857	38.18%	7.00	1.53	3.37	4.08	1.98	−0.01
T3 (most %affiliated ATS)	14711	21.29%	6.35	2.07	4.74	3.80	1.54	0.62
T1-T3		26.26%***	2.33***	−1.65***	−3.10***	−0.43**	−0.28	−0.85***
T2-T3		16.89%***	0.65***	−0.55***	−1.37***	0.28**	0.44***	−0.63***

Panel C: Medium stocks

Broker tercile	#Obs	Fill rate	Arrival spread (bp)	Eff. spread cost (bp)	Shortfall close (bp)	Shortfall cross (bp)	Drift (bp)	Post-drift (bp)
T1 (least %affiliated ATS)	18656	39.94%	32.86	0.85	2.89	11.43	2.97	−0.84
T2	19524	26.56%	32.89	2.56	6.87	16.15	3.98	0.94
T3 (most %affiliated ATS)	19202	15.06%	32.30	2.95	9.83	15.72	3.68	2.08
T1-T3		24.87%***	0.55	−2.10***	−6.94***	−4.30***	−0.71**	−2.92***
T2-T3		11.50%***	0.59	−0.39	−2.97***	0.43	0.30	−1.14***

Panel D: Small stocks

Broker tercile	#Obs	Fill rate	Arrival spread (bp)	Eff. spread cost (bp)	Shortfall close (bp)	Shortfall cross (bp)	Drift (bp)	Post-drift (bp)
T1 (least %affiliated ATS)	5543	38.28%	84.85	5.64	10.50	33.18	8.27	-1.10
T2	11027	23.44%	99.80	7.21	14.53	42.94	5.95	1.50
T3 (most %affiliated ATS)	11103	14.15%	113.93	5.47	20.07	50.93	6.16	3.85
T1-T3		24.13%***	−29.08***	0.17	−9.58***	−17.75***	2.11***	−4.95***
T2-T3		9.30%***	−14.13***	1.74**	−5.54***	−7.99***	−0.21	−2.36***

*p<0.1; **p<0.05; ***p<0.01

Table 5: ATS affiliation and execution quality, multivariate regression

This table presents results for multivariate regressions examining the relationship between ATS affiliation and execution quality. Units of observation are broker-stock-day top order quantity weighted averages. Each column corresponds to a regression specification. Dependent variables include: *Fill rate*, the ratio of executed quantity to top order quantity; *Effective spread cost*, the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker; *Shortfall close*, the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. The costs for the executed portion of the order is measured as in effective spread costs; *Shortfall cross*, the implementation shortfall calculated by imputing a fill at the opposing NBBO quote at the end of the order for the unexecuted portion of the order; *Drift*, the average signed NBBO midquote percentage return over the life of an order. The life of an order is measured from order arrival to the last observed event in the orders lifecycle; and *Post-drift*, the average signed NBBO midquote percentage return over the five minutes after the end of an order lifecycle. Independent variables include *%Affiliated ATS*, the percentage of routed quantity sent to affiliated ATSs; *order size*, the natural log of the average order size; *arrival spread*, the average percentage quoted NBBO spread at the time an order arrives at a broker; *post-drift*; *price*, the natural log of stock price; *market cap*, the natural log of market capitalization in thousands; and *RV*, the sum of squared five-minute midquote log returns. Test statistics are obtained from standard errors clustered by stock and day.

	Dependent variable:											
	Fill rate (%)				Eff. spread cost (bp)				Shortfall close (bp)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
%Affiliated ATS	-37.51^{***}	-37.37^{***}	-37.44^{***}	-37.30^{***}	-0.39	-0.33	-0.39	-0.33	6.22^{***}	5.77^{***}	5.93^{***}	5.48^{***}
Order size	1.33^{***}	1.32^{***}	1.28^{***}	1.28^{***}	1.04^{***}	1.04^{***}	1.09^{***}	1.09^{***}	1.78^{***}	1.80^{***}	1.83^{***}	1.85^{***}
Arrival spread (BP)	-0.05^{***}	-0.05^{***}	-0.06^{***}	-0.06^{***}	0.06^{***}	0.06^{***}	0.04^{***}	0.04^{***}	0.06^{***}	0.06^{***}	0.03^{*}	0.03^{*}
Post-drift (bp)		-0.04^{***}		-0.04^{***}		-0.02^{*}		-0.02^{*}		0.13^{***}		0.12^{***}
Price	-1.46^{***}	-1.46^{***}			0.32^{*}	0.32^{*}			0.17	0.23		
Market cap	2.27^{***}	2.27^{***}			-0.28^{***}	-0.28^{***}			-1.42^{***}	-1.44^{***}		
RV (bp)	-0.00	-0.00			0.00	0.00			-0.00			
Constant	2.64	2.75			-1.78	-1.73			14.84^{***}	14.75^{***}		
Stock Fixed Effects	*N*	*N*	*Y*	*Y*	*N*	*N*	*Y*	*Y*	*N*	*N*	*Y*	*Y*
Observations	139,265	139,265	139,265	139,265	122,981	122,981	122,981	122,981	139,265	139,265	139,265	139,265
Adjusted R^2	0.15	0.16	0.16	0.17	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.03

	Dependent variable:										
	Shortfall cross (bp)				Drift (bp)				Post-drift (bp)		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)
%Affiliated ATS	3.47^{***}	3.46^{***}	3.00^{***}	2.99^{***}	-3.19^{***}	-3.05^{***}	-3.10^{***}	-2.95^{***}	3.53^{***}	3.53^{***}	3.57^{***}
Order size	0.53^{***}	0.53^{***}	0.72^{***}	0.72^{***}	1.46^{***}	1.45^{***}	1.50^{***}	1.49^{***}	-0.20^{**}	-0.20^{**}	-0.19^{*}
Arrival spread (bp)	0.34^{***}	0.34^{***}	0.29^{***}	0.29^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.01^{*}	0.01^{*}	0.01
Post-drift (bp)		0.00		0.00		-0.04^{**}		-0.04^{**}			
Price	0.69^{***}	0.69^{***}			0.16	0.15			-0.14	-0.14	
Market cap	-1.40^{***}	-1.40^{***}			-0.77^{***}	-0.77^{***}			-0.08	-0.08	
RV (bp)	0.00^{***}	0.00^{***}			-0.00^{**}	-0.00^{**}			-0.00	-0.00	
Constant	18.59^{***}	18.58^{***}			6.18^{***}	6.29^{***}			2.68^{***}	2.68^{***}	
Stock Fixed Effects	*N*	*N*	*Y*	*Y*	*N*	*N*	*Y*	*Y*	*N*	*N*	*Y*
Observations	139,265	139,265	139,265	139,265	139,265	139,265	139,265	139,265	139,265	139,265	139,265
Adjusted R^2	0.43	0.43	0.44	0.44	0.01	0.01	0.01	0.01	0.00	0.00	0.00

*p<0.1; **p<0.05; ***p<0.01

Table 6: Persistence in execution quality

This table presents statistics of persistence in execution quality. Units of observation are broker-day averages across all stocks. Each day, brokers are sorted into terciles based on average deviations from a stock-day sample-wide benchmark of the proportion routed share quantity to affiliated ATSs. *Fill rate* is the ratio of executed quantity to top order quantity. *Effective spread cost* represents the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker. *Shortfall close* measures the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. The costs for the executed portion of the order is measured as in effective spread costs. *Shortfall cross* measures the implementation shortfall by imputing a fill at the opposing NBBO quote at the end of the order for the unexecuted portion of the order. *Drift* is the average signed NBBO midquote percentage return over the life of an order. The life of an order is measured from order arrival to the last observed event in the orders lifecycle. *Post-drift* is the average signed NBBO midquote percentage return over the five minutes after the end of an order lifecycle. Test statistics are obtained from standard errors clustered by broker and day.

	Day				
Variable	*T*	*T+1*	*T+2*	*T+3*	*T+4*
Tercile 1 (least %affiliated ATS)					
Fill rate (%)	47.19	47.13	46.62	45.98	47.00
Eff. spread cost (bp)	0.57	0.64	0.89	0.94	0.69
Shortfall close (bp)	4.08	3.66	3.21	3.26	3.00
Shortfall cross (bp)	7.15	6.94	7.55	7.54	7.12
Drift (bp)	2.17	1.87	2.43	2.31	2.00
Post-drift (bp)	−0.34	−0.42	−0.43	−0.07	−0.27
Tercile 2					
Fill rate (%)	39.70	40.28	40.42	40.67	40.15
Eff. spread cost (bp)	0.51	0.68	0.43	0.33	0.83
Shortfall close (bp)	4.62	5.01	5.40	4.78	5.37
Shortfall cross (bp)	14.48	14.84	14.17	14.32	14.78
Drift (bp)	2.87	3.48	2.88	3.08	3.45
Post-drift (bp)	−0.06	0.30	0.32	−0.22	0.07
Tercile 3 (most %affiliated ATS)					
Fill rate (%)	26.14	25.86	25.99	25.99	25.83
Eff. spread cost (bp)	3.22	3.11	3.15	3.35	3.28
Shortfall close (bp)	8.91	9.11	8.88	9.24	8.89
Shortfall cross (bp)	17.44	17.62	17.59	17.76	17.80
Drift (bp)	3.25	3.27	3.31	3.62	3.54
Post-drift (bp)	1.61	1.54	1.52	1.44	1.27
T3-T1 (Fill rate)	−21.05**	−21.27**	−20.63**	−20.00**	−21.18**
T3-T1 (Eff. spread cost)	2.65***	2.47**	2.26**	2.41**	2.59**
T3-T1 (Shortfall close)	4.83***	5.45***	5.67***	5.98***	5.90***
T3-T1 (Shortfall cross)	10.29***	10.68***	10.04***	10.22***	10.68***
T3-T1 (Drift)	1.07	1.40	0.89	1.30	1.54
T3-T1 (Post-drift)	1.95***	1.96***	1.95***	1.51**	1.53**
T3-T2 (Fill rate)	−13.56*	−14.42*	−14.43*	−14.69*	−14.33*
T3-T2 (Eff. spread cost)	2.72*	2.43**	2.73**	3.02**	2.45**
T3-T2 (Shortfall close)	4.29**	4.10**	3.48**	4.47***	3.52***
T3-T2 (Shortfall cross)	2.96	2.78	3.42	3.44	3.03
T3-T1 (Drift)	0.38	−0.22	0.43	0.53	0.09
T3-T2 (Post-drift)	1.67**	1.24*	1.20	1.67**	1.19

*p<0.1; **p<0.05; ***p<0.01

Table 7: ATS affiliation and execution quality, matched analysis

This table presents results for matched analysis controlling for ATS routing. Units of observation are broker-stock-day top order quantity weighted averages. Tercile 3 (*T3*, characterized by the most routing to affiliated ATSs) brokers are matched with a T1 or T2 broker on the same stock-day based on the percentage of share quantity routed to ATSs using nearest neighbor one-to-one propensity score matching using a caliper of 0.25 of a standard deviation. Panel A presents statistics of the full and matched sample. Treatment brokers are T3 brokers and control brokers are T1 or T2 brokers. *%ATS* is the average percentage of routed quantity sent to ATSs. *%Affiliated ATS* is the average percentage of routed quantity sent to affiliated ATSs. *%Unaffiliated ATS* is the average percentage of routed quantity sent to unaffiliated ATSs. *Order size* is the average order size. *Volume* is the average daily trading volume. *Price* is the average stock price. *Market cap* is the average market capitalization. Panel B presents results for the matched regression analysis. Dependent variables include: *Fill rate*, the ratio of executed quantity to top order quantity; *Effective spread cost*, the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker; *Shortfall close*, the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. The costs for the executed portion of the order is measured as in effective spread costs; *Shortfall cross*, the implementation shortfall calculated by imputing a fill at the opposing NBBO quote at the end of the order for the unexecuted portion of the order; *Drift*, the average signed NBBO midquote percentage return over the life of an order. The life of an order is measured from order arrival to the last observed event in the orders lifecycle; and *Post-drift*, the average signed NBBO midquote percentage return over the five minutes after the end of an order lifecycle. Independent variables include *T3*, an indicator variable that is equal to one for a treatment broker and zero otherwise; *order size*, the natural log of the average order size; *arrival spread*, the average percentage quoted NBBO spread at the time an order is placed with a broker; and *post-drift*. Test statistics are obtained from standard errors clustered by stock and day.

Panel A: Descriptive statistics

	#Observations		#Brokers		%ATS		%Affiliated ATS		%Unaffiliated ATS	
	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
Full sample	94249	45016	34	9	17.63%	63.64%	3.18%	49.87%	14.45%	13.76%
Matched sample	19274	19274	34	9	50.05%	51.20%	7.17%	41.53%	42.88%	9.67%

	#Stocks		Order size		Volume (mm)		Price ($)		Market cap ($mm)	
	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
Full sample	273	273	1724.37	631.71	3844.41	2671.26	61.71	54.68	44599.54	30251.14
Matched sample	273	273	3080.60	691.84	3239.35	3239.35	54.84	54.84	35036.66	35036.66

Panel B: Matched regression

	Dependent variable:										
	Fill rate (%)		Eff. spread cost (bp)		Shortfall close (bp)		Shortfall cross (bp)		Drift (bp)		Post-drift (bp)
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)
T3	−5.66***	−5.64***	−1.30*	−1.29*	1.98***	1.95**	1.13*	1.13*	1.61***	1.63***	0.35
Order size	3.63***	3.62***	0.19	0.18	1.60***	1.63***	1.35***	1.34***	1.72***	1.71***	−0.36
Arrival spread (bp)	−0.05***	−0.05***	0.04*	0.04*	0.08***	0.08***	0.30***	0.30***	0.07***	0.07***	0.01
Post-drift (bp)		−0.04**		−0.03		0.09**		−0.01		−0.05	
Match Pair Fixed Effects	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	38,548	38,548	32,502	32,502	38,548	38,548	38,548	38,548	38,548	38,548	38,548
Adjusted R^2	0.33	0.33	0.10	0.10	0.16	0.16	0.54	0.54	0.02	0.03	0.22

*p<0.1; **p<0.05; ***p<0.01

Table 8: Horse races

This table presents results for horse races of ATS midpoint pegged orders. Affiliated routes of Tercile 3 (T3, characterized by the most routing to affiliated ATSs) brokers are matched with routes to unaffiliated ATSs. A horse race involves a pair of ATS midpoint pegged orders that have the same stock, date, order side, arriving during the same NBBO price state. The first order in the order pair must still be active, unmodified, and not have obtained an execution when the second order in the order pair is routed. Descriptive statistics of the order pairs are presented in Panel A. *Avg. affiliated fill rate* is the average fill rate of matched affiliated child orders. *Avg. unaffiliated fill rate* is the average fill rate of matched unaffiliated child orders. *Both fill* is the percentage of horse races in which both orders in the pair obtain a fill. Panel B presents results for horse races. *Affiliated fill first* is the percentage of horseraces in which the affiliated route filled more than 500ms prior to its paired order. For this analysis, a fill occurs when any part of the route receives an execution. *Unaffiliated fill first* is the percentage of horseraces in which the unaffiliated route filled more than 500ms prior to its paired order. *Tie* is the percentage of horseraces in which the affiliated route filled within 500ms of its paired order. Results are presented for all pairs and for pairs in small (smallest 30%), medium (middle 40%), and large (largest 30%) market capitalization stocks. Signifiers *,** ,*** indicate that differences between affiliated and paired outcomes are statistically significant at the 10%, 5%, and 1% level, respectively. Test statistics are obtained from standard errors clustered by stock and day.

Panel A: Descriptive statistics

Matched pair type	# of order pairs	Avg. affiliated fill rate	Avg. unaffiliated fill rate	Both fill
All horse races	1421432	41.10%	50.08%***	11.51%
Large stocks	1308126	41.16%	50.24%***	11.74%
Medium stocks	107015	40.47%	48.37%***	8.71%
Small stocks	6291	40.01%	45.39%**	12.19%

Panel B: Horse races

Matched pair type	Affiliated fills first	Unaffiliated fills first	Tie
All horse races	41.92%	53.31%***	4.76%
Large stocks	41.75%	53.42%***	4.83%
Medium stocks	43.83%	52.27%***	3.90%
Small stocks	45.59%	48.64%	5.77%

*p<0.1; **p<0.05; ***p<0.01