Institutional Order Handling and Broker-Affiliated Trading Venues *

Amber Anand
Syracuse University

Mehrdad Samadi
Southern Methodist University

Jonathan Sokobin
FINRA

Kumar Venkataraman
Southern Methodist University

Using detailed order handling data, we find that institutional brokers who route more orders to affiliated alternative trading systems (ATSs) are associated with lower execution quality (i.e., lower fill rates and higher implementation shortfall costs). To separate clients' preference for ATSs from brokers' routing decisions, we confirm these results for orders where brokers have more order handling discretion, matched broker analysis that accounts for ATS usage, matched child orders that account for client intent, and based on an exogenous constraint on ATS venue choice. Our results suggest that increased transparency of order routing practices will improve execution quality. (*JEL* G10, G20)

* We thank Lore Aguilar, Robert Battalio (UBC discussant), Jonathan Brogaard (Sydney discussant), Tom Bruno, Robert Colby, Stephanie Dumont, Amy Edwards, Alexander Ellenberg, Harry Feng, Thomas Gira, Itay Goldstein (the Editor), Michael Goldstein, Clifton Green (EFA discussant), Charles Jones, Swami Kalpathy, Eric Kelley (MARC discussant), Pete Kyle, Laurence Lescourret (WFA Discussant), Craig Lewis, Esen Onur (Erasmus discussant), Kapil Phadnis, Dan Royal, Gideon Saar (NBER discussant), Gary Stone, Larry Tabb, Laura Tuttle (CFMR discussant), Scott Trilling, David Saltiel, George Sofianos, and Ingrid Werner (FINRA-EAC discussant) and two anonymous referees for their comments. We also acknowledge comments received at FINRA's Economic Advisory Council meeting, Mid-Atlantic Research Conference, NBER conference on Big Data: Long-term implications for financial markets and firms, Conference on Financial Market Regulation, Western Finance Association, European Finance Association, Erasmus Liquidity Conference, University of British Columbia Winter Finance Conference, and the Sydney Microstructure Conference. We also thank seminar participants at AQR, Southern Methodist University, Syracuse University, University of Melbourne, University of New South Wales, UMass Amherst, and University of Technology Sydney. We are grateful to Shelly Bohlin, Megha Kampasi, Katie Madison, and Laura Shoemaker for their generous help with data related clarifications. Anand, Samadi, and Venkataraman are adjunct researchers with the Office of Chief Economist at FINRA. The views expressed in this paper are those of the authors and do not necessarily reflect the views of FINRA or of the authors' colleagues on the staff of FINRA. Send correspondence to Kumar Venkataraman, kumar@smu.edu.

Institutional investors account for a majority of ownership of U.S. 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 et al. (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, including splitting an institutional order into smaller pieces, selecting among execution venues, and sequencing the submission of the split 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 U.S. equity market structure makes it difficult for institutions to assess broker performance, especially since routing data are either unavailable or difficult to decipher.[2]

Further, opaque reporting practices on the handling of institutional orders can obscure potential agency conflicts that influence broker routing decisions. A report by the International Organization of Securities Commissions (IOSCO 2017) identifies three incentives that may influence broker behavior: monetary benefits received from third parties; bundling of other client services with executions; and affiliated venues that have benefits for brokers.

Battalio, Corwin, and Jennings (2016) study the impact of monetary benefits related to exchange pricing models on broker routing. They note that fees and rebates to brokers from venues are not generally passed on to clients. The study finds that routing of nonmarketable retail orders to venues with higher rebates hurts execution quality. Bundling ancillary services ("soft dollars"), such as research and initial

[1] Anand et al. (2012) estimate average institutional trading costs of 25 bps over 1999 to 2008. ITG, Inc., reports average U.S. equity execution costs of 23 bps in Q2 2017 (https://www.itg.com/assets/ITG_Global-Cost-Review-2017Q2-Prelim-BrokerCostUpdated.pdf). Busse et al. (2020) estimate that trading costs accumulate to 0.75% per year for actively managed mutual funds.

[2] Securities and Exchange Commission (SEC) Chair Mary Jo White (2016) has said: "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."

public offering (IPO) allocations, alongside order execution, raises the possibility that clients are less likely to select brokers based on the quality of executions. Consistent with this idea, 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 a largely unstudied potential source of agency conflict, namely, broker routing of client orders to alternative trading systems (ATSs) that they own ("affiliated ATS"). We study two questions: Do brokers show a preference for routing orders to an affiliated ATS? Is there a systematic association between affiliated ATS routing preference and execution quality? We recognize that routing decisions may reflect differences in broker clientele or a client's preference for ATS venues and present several approaches to isolate the impact of a broker's routing decisions on execution quality.

Venue ownership can influence the broker's routing decisions in several ways. A broker pays fees to place and execute orders on trading venues, but, typically, these fees are not passed on to clients. A broker avoids paying these fees on affiliated venues. The fee savings create a conflict between obtaining the best outcome for the client and maximizing broker revenues.[3] Brokers obtain additional benefits from higher volume on affiliated venues. Other participants (including liquidity providers) typically pay fees to the ATS operator for executing orders on the ATS. Higher ATS volume is a mark of success that attracts order flow, and can be a selling point to clients, thus, increasing market share and commissions earned. Higher ATS volumes can boost the brokerage firm's rankings in a stock's trading, which can help the investment banking arm win corporate finance engagements with the issuer. For these reasons, a broker may prefer an affiliated ATS over other venues even when such a preference is not optimal for the client.[4]

On the other hand, brokers have a duty of best execution to clients, a duty that generally requires brokers to seek as favorable of executions as possible under prevailing market conditions. Routing to an

[3] The ATS operator and the participant negotiate fees. NYSE estimates a fee of $0.0010 per share for trading on an ATS (https://www.nyse.com/equities-insights#20181107). A similar trade-off applies to trading the client's order on an exchange based on the net fees (the difference between the fee and the rebate).
[4] The NY Attorney General (2014) notes that, for one broker, opportunities related to having a successful ATS and "market share value of attracting more [order] flow" were valued between $37 million and $50 million per year.

affiliated ATS can improve client outcomes in several ways. A broker can efficiently source liquidity from an affiliated ATS if the ATS order book information is visible to the broker's smart order router. Competing brokers may have limited access to a broker's affiliated ATS, thus, the affiliated ATS offers an additional venue to the client. Other often-noted benefits of ATSs over exchanges include the potential for price improvement, and the ability to hide orders, limit price impact, and interact with select participants (see IOSCO 2017). Given these potential benefits, it is unclear whether, and how, routing to affiliated ATSs affects execution quality of client orders.

To the best of our knowledge, no existing empirical work examines the relation between broker routing, venue ownership, and execution outcomes. The lack of research is likely due to insufficient suitable data. In this study, we use the FINRA Order Audit Trail System (OATS) database that provides detailed information on orders received by brokers from their clients (henceforth "top orders"), including the identity of the broker; the venue-specific routing decisions; and the venue-specific outcomes, such as executions, traded prices, and time stamps associated with each routing, modification, execution, or cancellation decision in an order's life cycle. The OATS database, created for regulatory purposes, covers a comprehensive cross-section of brokers and does not suffer from attrition or sample selection bias issues that often affect data received from a subset of industry participants.[5] We study a sample of over 350 million top orders that are received by 43 active institutional brokers for a size-stratified sample of 300 stocks in October 2016.

We find that not all brokers that own an ATS route more orders to the affiliated venue. We calculate the average deviation between a broker's routing to an affiliated ATS and the aggregate comparable statistic for all brokers on a stock-day. Based on this measure, we place the brokers into three groups. For brokers in the highest tercile (T3), routing to ATSs accounts for 63% of the routed quantity, largely attributable to affiliated ATS routes (50% of the routed quantity), while for brokers in middle (T2) and lowest (T1) terciles, routing to ATSs (affiliated ATS) accounts for 26% (6%) and 9% (0%) of the routed quantity. The affiliated

[5] Einav and Levin (2014) and Card et al. (2010) advocate for the use of such administrative data in economic analyses.

ATS accounts for 17% of the executed quantity for T3 brokers. For perspective, in the fourth quarter of 2016, an individual ATS typically executed less than 1%, and the combined market share of all ATSs is less than 14%.[6] Thus, T3 brokers route and execute more orders on affiliated ATSs.

We find that higher affiliated ATS routing is associated with lower execution quality. These results are observed for the "fill rate" measure, defined as the ratio of executed shares to the submitted quantity for a top order, and execution cost measures based on the implementation shortfall (IS) approach, which accounts for fill rates, market impact, and price drift (see Perold 1988; Wagner and Edwards 1993). The OATS database does not include client identifiers or information on a client's trade motive or certain order instructions. Consequently, we report several shortfall measures that reflect a range of assumptions about the client's opportunity costs of unfilled orders.[7]

After controlling for stock characteristics, order attributes and market conditions, a one-standard-deviation increase in affiliated ATS routing is associated with an 11.6-percentage-point decline in fill rates. In similar regressions, higher affiliated ATS routing is associated with higher implementation shortfalls. We find robust evidence across the different approaches used to impute an execution price for the unfilled portion of the top order ("cleanup" costs). We find that the higher shortfall costs stem from higher delay costs (price drift and cleanup costs).

The theoretical model in Ye and Zhu (2019) predicts that large traders prefer ATSs when they have more information. Thus, the lower execution quality for T3 brokers can stem from a selection bias, where clients with more difficult or informed orders cluster with T3 brokers. The regression specifications include

[6] Estimates are based on FINRA ATS Transparency Data Quarterly Statistics available at https://www.finra.org/filing-reporting/otc-transparency/ats-quarterly-statistics.

[7] 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 price for the unfilled portion of the order based on different assumptions. For our main analysis, imputed executions are based on the closing price of the trading day. In Internet Appendix Table A1, we include shortfalls using imputed executions at the prevailing opposite NBBO quote (i.e., prevailing best quoted ask [bid] price for buys [sells]) at the end of the life cycle, or the volume weighted average price (VWAP) calculated from TAQ data from the end of the life cycle to the end of the trading day. We also report effective spread costs, following the terminology in Perold (1988), which assumes that the opportunity cost of the unfilled portion of an order is zero.

reasonable controls for order difficulty; however, as the data do not allow an explicit control for client identity, we implement several approaches to mitigate this concern.

We examine the effect of broker discretion in handling orders based on "not-held" designation in OATS data.[8] In a difference-in-differences specification, not-held orders (i.e., those with greater broker discretion) are associated with worse execution outcomes, such as lower fill rates and higher shortfalls, than held orders for T3 brokers relative to non-T3 brokers. These results suggest that execution quality differences for T3 brokers can be attributed, at least in part, to the brokers' routing decisions.

To address the possibility that more difficult orders are sent to ATSs we implement a matched broker analysis where the broker pairs have a similar level of ATS routing (about 50% of routed volume) on the same stock-day. In the matched pairs, T3 brokers predominantly route (42% of routed volume) to their affiliated ATSs while non-T3 brokers predominantly route (43% of routed volume) to unaffiliated ATSs. The analysis controls for a selection bias where clients prefer ATS venues for difficult orders and helps isolate the impact of *affiliated* ATS routing on execution quality. In the matched regressions, T3 brokers have fill rates that are 5.4 percentage points lower and shortfall costs that are 2.2 basis points (bps) higher than their matched non-T3 brokers.

T3 brokers' routes to affiliated ATSs may possibly occur in more difficult conditions than other ATS routes. To the extent that order difficulty is associated with market conditions (e.g., one-sided imbalances), do we observe higher ATS usage by T3 brokers when conditions are difficult? We find that T3-affiliated ATS executions are more likely in easier conditions than non-T3 ATS executions. The empirical determinants of ATS routing are markedly different than those of ATS executions: non-T3 brokers are more likely to route to ATSs under difficult conditions, while T3-affiliated ATS routes are largely insensitive to market conditions. These results do not suggest that T3 brokers route more orders to affiliated ATSs under relatively difficult conditions.

[8] According to the SEC (2018), "typically, a "not-held" order provides the broker-dealer with price and time discretion in handling the order, whereas a broker-dealer must attempt to execute a "held" order immediately."

Zhu (2014) and Reed, Samadi, and Sokobin (2020) uncover significant variety in features across ATSs. We examine whether affiliated ATSs of T3 brokers exhibit design features that are less likely to be associated with information leakage, which is a concern for informed investors. For most ATSs, we rely on Reg ATS-N filings available on the SEC's website.[9] We create an ATS *Opacity* measure based on one/zero scores for characteristics that make an ATS less opaque (e.g., the presence of affiliated principal traders or external proprietary traders) and those that make an ATS more opaque (e.g., the ability to exclude counterparties). We do not observe significant differences in ATS *Opacity* measure between T3-affiliated ATSs and other ATSs. Thus, it does not appear that, all else equal, T3-affiliated ATSs offer design features that are more attractive in terms of opacity to informed investors.

We exploit the granularity of the data in order to examine route-level outcomes for commonly used order types across ATSs, which more precisely control for order type, market conditions and client intent. Specifically, we adapt the paired route "horse race" approach developed by Sofianos, Xiang, and Yousefi (2010) and 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 matched separately for two common order types: midpoint peg orders and primary peg orders. Midpoint pegs are limit orders that dynamically update their price to the NBBO midpoint, while primary pegs are tied to the passive side of the NBBO. The paired child orders are open at the same time, which controls for market conditions, and have the same order instructions, which accounts for client intent and the type of ATS venue. For both midpoint and primary peg orders, we find strong evidence that unaffiliated ATS routes have higher fill rates and obtain an earlier fill than matched T3-affiliated ATS routes. The horse race results point to a potential mechanism to understand the execution quality differences observed in the broader sample.

To further address the possibility that our results reflect clients placing more difficult orders with T3 brokers as opposed to agency conflicts, we study broker routing and execution quality surrounding a

[9] These filings were required beginning in 2019. ATS features may have changed since our sample period in 2016.

regulatory experiment likely to affect venue choice: the SEC's implementation of the Tick Size Pilot (TSP) program in October 2016, which significantly constrained executions at ATSs that match orders at the quotes for a randomly assigned subset (treatment group 3) of stocks. We test the following competing hypotheses: if T3-affiliated ATS routing is associated with optimal routing, then, relative to non-T3 brokers, T3 brokers' execution outcomes will *worsen* when venue choice is constrained. On the other hand, the TSP may help resolve agency conflicts as some ATSs become less viable destinations, implying that T3 brokers' execution outcomes will *improve* relative to non-T3 brokers. Based on a triple difference analysis that compares T3 versus matched (based on overall ATS routing in the pre-TSP period) non-T3 brokers, in group 3 (G3) stocks versus control stocks, before and after the implementation of the TSP program, we find support for the agency conflict hypothesis in that the outcomes for T3 brokers for G3 stocks improve relative to non-T3 brokers after the TSP is implemented. Since we retain our brokers and their tercile classifications from the main analysis, the TSP analysis also provides a useful out-of-sample test of the main findings of the study.

The collective evidence from various approaches suggests that the execution quality differences for T3 brokers are consistent with agency conflicts that lead brokers to route more orders to their affiliated ATSs. Structural changes in equity markets have increased the challenges faced by institutions in measuring broker performance. The proliferation of trading venues has fragmented markets and decreased the transparency of brokers' routing decisions.[10] Our results indicate that institutions will benefit from recent regulatory and industry initiatives aimed at increasing transparency of order handling.

We caution that ownership of a venue alone does not constitute evidence of routing conflicts; indeed, not all brokers that own an ATS show a preference for their venues, and not all orders routed to an

[10] Institutional investors' concerns are the impetus behind the SEC's (2016) initiative to add transparency to the handling of institutional order flow (see pp. 11, 33-34): "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."

affiliated ATS exhibit worse execution quality. We recognize that institutions receive benefits from brokers that extend beyond execution services, and that commissions could be systematically lower for T3 brokers. In those cases, our study provides information on execution quality outcomes that institutions can compare with the value of bundled services or commission savings received from brokers.

1. Venue Selection, Broker Handling and Agency Conflicts

A typical institutional trading decision starts with a portfolio manager. These decisions flow to the institutional trading desk, where they are consolidated across portfolio managers. The trading desk decides how to slice the order and allocate the slices to brokers, increasingly through a broker algorithm. These allocated orders are defined in our analysis as a client-broker top orders. The broker (algorithm) typically splits the top order into smaller pieces and generates a mix of child orders over time. The child order generation depends on several decisions related to the child order size, timing, aggressiveness, the venues to access and whether venues are accessed sequentially or in parallel. The combination of these decisions makes order handling difficult to monitor and evaluate, especially since trading is fragmented across 13 exchanges and more than 40 ATSs during our sample period.[11] The institution typically pays a fixed commission to the broker for handling the order. According to Tabb group estimates, brokerage commissions for algorithmic executions have steadily declined from an average of $0.019 per share in 2005 to $0.0060 in 2017.[12]

One dimension of the routing decision is the choice between seeking executions on (relatively opaque) ATSs and (relatively transparent) exchanges. ATSs do not publicly display orders, typically use prices derived from displayed exchange quotes, and report trades through trade reporting facilities, which

[11] The SEC (2016) notes that, "Although certain advantages flow from technological advancements and the increase in number of venues, the Commission preliminarily believes that the complexity of order execution algorithms and smart order routing systems, and the multiplicity of venues to which broker-dealers may route orders or send actionable indications of interest, have made it increasingly difficult for institutional customers to assess the impact particular order routing strategies may have on the quality of their executions, or the risks presented by any resulting information leakage or broker-dealer conflicts of interest."
[12] We are grateful to Larry Tabb for sharing his data on broker commissions.

combine all nonexchange trading (ATS and wholesaler executions), thus obscuring venue identity.

The theoretical literature has modeled the strategic venue selection by informed traders between ATS venues and "lit" exchanges.[13] Based on the Kyle (1985) framework, Ye (2011) and Ye and Zhu (2019) model the monopolist informed traders' choice. In Ye and Zhu (2019), traders choose between the higher cost of paying for immediacy on an exchange (where a market maker provides liquidity) against the higher risk of nonexecution on an ATS. The model predicts that the informed traders prefer an ATS because trading on the exchange moves the price, which hurts the execution quality on the ATS, particularly when the trader wants to acquire a large position.[14] In a setting with competition among informed traders, the model in Zhu (2014) highlights that informed traders with correlated information tend to cluster on the same side of the ATS and suffer from lower execution probability. The model predicts that informed traders avoid ATSs when they have information due to costly delays in execution. Given that our study examines institutional brokers, the Ye and Zhu (2019) framework has particular relevance, since institutions are sensitive to the price impact of their large orders.

Depending on model assumptions, theory offers opposing predictions on whether institutions prefer ATSs when they have more information. Regardless of the direction, since less informed trades have lower execution costs, the relation between information and ATS routing potentially introduces a selection bias, since a broker's client mix may be associated with higher ATS routing. Our data constraints prohibit us from identifying the institutional trader; however, we present several empirical approaches to account for selection bias and isolate the impact of a broker's ATS routing preference on execution quality.

Other theoretical papers model strategic venue selection in a setting without asymmetric information. Degryse, Van Achter, and Wuyts (2009) predict that traders prefer an ATS to a dealer market when the bid-ask spread is large, as ATSs provide a greater potential for price improvement. Buti, Rindi,

---

[13] Traders can hide their trading interest on exchanges by posting hidden orders. Bloomfield, O'Hara, and Saar (2015) provide an experimental analysis of trader strategies and market impact in the presence of hidden trading. Hasbrouck and Saar (2002) document completely hidden orders, and Anand and Weaver (2004) and Bessembinder, Panayides, and Venkataraman (2009) examine partially hidden ("iceberg") orders.
[14] Using trades from activist investors reported in Schedule 13F filings, the study finds that increases in an activist's information leads to more trades on ATSs.

and Werner (2017) offer the opposite prediction that traders prefer an ATS when limit order book is well populated, as the limit order queue at the best bid and offer is longer. Buti, Rindi, and Werner (2016) and Ready (2014) report empirical support for the latter model. Menkveld, Yueshen, and Zhu (2017) offer a pecking order hypothesis where an investor prefers a lit exchange to ATSs when the trading needs become more urgent and report empirical support for the model. Based on the literature, it is likely that investors favor trading on ATSs over exchanges under certain conditions. For this reason, our empirical analysis includes several approaches to account for order difficulty and market conditions.

Finally, venue selection can be influenced by private benefits that accrue to brokers. In the presence of agency conflicts, a broker's propensity to route orders to affiliated ATSs could lead to worse outcomes for clients. In this context, this study is related to the literature on brokers' routing of order flow pursuant to monetary benefits from third parties.[15]

For retail orders, Battalio, Corwin, and Jennings (2016) show that order routing designed to maximize a broker's liquidity rebates on exchanges does not maximize limit order execution quality. A number of recent studies examine the interactions between institutional orders, high frequency traders (HFT) and execution quality.[16] This literature links the market impact of institutional orders to HFT "back-runners" who detect order flow "footprints" and trade ahead or alongside institutional investors (for theory, see Yang and Zhu 2020; for evidence, see Kirilenko et al. 2017; van Kervel and Menkveld 2019; Saglam 2018; and Korajczyk and Murphy 2019). Battalio, Hatch, and Saglam (2018) attribute higher institutional trading costs to information leakage that stems from early routes to high frequency liquidity providers.

2. Data and Sample Description

2.1. Data sources and sample

[15] With respect to retail order flow, Easley, Kiefer, and O'Hara (1996) provide evidence that payment for order flow arrangements siphon uninformed order flow away from public markets. Battalio (1997) and Battalio et al. (2002) report that these arrangements are not associated with a deterioration in execution quality or quote competitiveness across venues.

[16] Hendershott, Jones, and Menkveld (2011), Brogaard, Hendershott, and Riordan (2014), Brogaard et al. (2015), and Boehmer, Li, and Saar (2018) find that HFTs are associated with improved market quality and higher price efficiency.

The primary data set used in the study is the FINRA OATS database for the month of October 2016. Almost every broker-dealer in the United States is required to report audit trail information on equity orders to FINRA.[17] For each broker-level parent order ("top order") received from a client, OATS provides information detailing how the broker handled the top order. The data set combines the identity of the broker handling the order, the beneficiary owner type, and the submitted quantity of the broker-level order, with the audit trail of routes, venues, executions, modifications, and cancellations associated with the order's life cycle.[18]

The OATS 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 academic data made available by Abel-Noser Solutions that were used by Puckett and Yan (2011) and Anand et al. (2012, 2013). A limitation of the OATS data is that, while we observe orders handled by a broker for an institution (i.e., top order), it is not possible to further stitch together orders split by an institution across multiple brokers or submitted to the same broker at a later time. A significant advantage of the OATS data is the detailed information on a comprehensive cross-section of brokers' handling of top orders and the venue-level routes and execution outcomes, which are not available in other databases.[19] Further, comprehensive administrative data help overcome concerns related to selection bias that often affect studies that examine data from a subset of market participants.

The appendix describes our selection of 43 large institutional brokers. We use the beneficiary owner classification field from OATS, along with institutional broker classification of Griffin et al. (2011) to identify institutional brokers. The beneficiary owner field indicates whether an order represents

[17] Broker-dealers in the United States 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. 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.

[18] Werner (2003) uses an earlier iteration of OATS to analyze 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 and the number of orders is significantly larger.

[19] OATS provides the most comprehensive audit trail of orders across brokers and venues. However, as the SEC (2018, p. 201) notes, currently there is no reporting in any regulatory database of indications of interest (IOIs). IOIs can be used by brokers to solicit liquidity for the orders they have received.

institutional, individual, market maker, proprietary interest, or is unknown. Griffin et al. (2011), classify institutional brokers based on “company web pages, news media, the NASD website, and conversations with NASDAQ officials.” We exclude brokers that are primarily associated with internalized flow or serve as conduits, sending 100% of received order flow to a single ATS. We focus on “active” institutional brokers that handle at least 10,000 top orders in October 2016. 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.[20]

For a part of the analysis, we use the “not-held” order handling code in OATS data to identify top orders from institutions where the broker has price and time discretion (within client-specified constraints) in handling the order. The not-held order code is well established and clearly understood within the industry. In response to SEC’s proposed order disclosure rule, several industry participants recommend the use of not-held designation to differentiate institutional from retail flow and the need for enhanced disclosure for these orders.[21] SEC (2018) incorporates this recommendation and focuses on the not-held versus held distinction for the revised order handling disclosures for brokers. On the other hand, we do not differentiate between “directed” and “nondirected” orders. Directed orders are those where the client specifies the venue, thus limiting the broker’s discretion on venue selection. At first glance, the nondirected orders seem to be obvious choice for our analysis. However, during our sample period, the Rule 606 definition of orders makes such an analysis difficult.[22] Specifically, a broker can flag an order as directed if a client does not change the default venue choice in the broker’s algorithm, which makes it difficult to identify venue choices

[20] We examine direct ownership of an ATS where potential private benefits are largest. Consortium-owned ATSs are not classified as affiliated in our study.
[21] See, for example, Markit (2016), Blackrock (2016), Financial Information Forum (2016), and Capital Group (2016). Consistent with the expectation that institutional orders are primarily not-held, a majority (65%) of our sample orders carry the not-held designation.
[22] The old Rule 606 required brokers to produce quarterly disclosures of venue routing for nondirected orders only (i.e., directed orders were excluded). Consistent with the cleaner not-held versus held separation, the revised Rule 606 drops the nondirected requirement and instead focuses on the not-held marking for these quarterly disclosure reports.

that are truly determined by the client.[23] With those caveats, we confirm that the main results are observed for the sample of nondirected orders in Internet Appendix Table A2.

Our sample consists of a size-stratified group of 300 stocks traded in October 2016, a recent month when the project was initiated.[24] In light of the size of OATS database, we form decile portfolios using CRSP data on market capitalization at the end of December 2015 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 a number of data filters to obtain a final sample as detailed in the appendix. 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 350 million life cycles of the top orders received by the 43 institutional brokers in the sample stocks.

The Tick Size Pilot (TSP) program was implemented by the SEC in October 2016. We obtain qualitatively similar results when we restrict the sample to stocks unaffected by the TSP. To assess the impact of the TSP program, we separately examine data from September and November of 2016 using group 3 stocks (as defined in the TSP) as the treated sample and group 2 stocks and the TSP control stocks as separate control samples. After applying the filters detailed in the appendix, the TSP sample includes 898 million total life cycles associated with the 43 brokers in 247 G3 stocks, 257 G2 stocks and 811 control stocks.

2.2. Measures of execution quality

The first measure of execution quality, the *fill rate* is the filled quantity divided by the submitted

[23] See https://www.sec.gov/interps/legal/mrslb13a.htm#q3. Further, if the order does not execute on the venue and is rerouted by the broker, it is still considered a directed order. To illustrate the issue, we pick the 10 brokers listed as leaders among the "US equity trading share," the "US equity algorithmic trading share," the "US equity research advisory vote share," and the "Global portfolio trading share" in the 2015 Greenwich Associates survey of U.S. equities brokers (https://www.greenwich.com/equities/top-four-us-equity-brokers-distance-themselves-pack). We examine a sample of 606 reports around our sample period for these brokers. The proportion of nondirected orders for these brokers in these reports range from 3.3% to 99.75%, with an average of 40.6%. Three of the ten brokers report proportions of nondirected orders of less than 5%.

[24] Two relevant market developments are noteworthy. First, the SEC's scrutiny of ATS operators was marked by settlements with Barclays and Credit Suisse in January 2016. Second, FINRA required separate identifiers for ATSs (from broker identifiers) starting in 2015.

quantity of a top order. In the IS approach, orders with fill rates below 100% incur an opportunity cost for the unfilled portion of an order (see Perold 1988, Wagner and Edwards 1993). We employ four 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 life cycle *i* received by broker *b* is calculated as follows:

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

where $P_{1(b,i)}$ is the share volume-weighted execution price, $P_{0(b,i)}$ is the benchmark price, 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.

We present three approaches to impute execution for unfilled portion of order, as follows:

$$\textit{Shortfall}_{(b,i)} = \left[f_{(b,i)} \times \frac{P_{1(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right] + \left[(1 - f_{(b,i)}) \times \frac{IP_{(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right], \quad (2)$$

where $f_{(b,i)}$ is the *fill rate* of the top order, $IP_{(b,i)}$ is the imputed price for unfilled portion of the order, and other variables are defined above. For our primary measure, *Shortfall*, $IP_{(b,i)}$ is the closing price obtained from CRSP, following the approach in Keim and Madhavan (1997) and Conrad, Johnson, and Wahal (2001), which reflects the assumption that traders are able to fill the unfilled portion at the close. *Shortfall cross* follows Harris and Hasbrouck (1996) and Handa and Schwartz (1996) and assumes that the unfilled portion is filled at the opposite quote at the end of the life cycle; that is, $IP_{(b,i)}$ is the ask (bid) quote for buy (sell) orders at the time of the last event in the order's life cycle. For *Shortfall VWAP*, $IP_{(b,i)}$ is the volume-weighted average price (VWAP) based on TAQ reported trades that are not corrected or canceled with an execution price greater than zero between the end of the life cycle and the closing trade print. The measure assumes that traders participate alongside the market for the unfilled portion of the order.

In their analysis of venue fees, Sofianos, Xiang, and Yousefi (2011) report that the important driver of shortfall is the cost of delayed executions, that is, adverse price movements and cleanup costs. We term this component as "delay" and calculate the measure, analogous to shortfall costs, as follows:

$$Delay = \left[f_{(b,i)} \times \frac{P_{2(b,i)} - P_{0(b,i)}}{P_{0(b,i)}} \times D_{(b,i)}\right] + \left[(1 - f_{(b,i)}) \times \left(\frac{IP_{(b,i)} - P_{0(b,i)}}{P_{0(b,i)}}\right) \times D_{(b,i)}\right], \quad (3)$$

where $P_{2(b,i)}$ is the executed share volume-weighted NBBO midpoint at the time of execution.

2.3. Descriptive statistics

Table 1 describes the sample. For each broker-stock-day, we calculate the weighted average of the order characteristics and market quality measures across top orders, where the weights are the quantity of the top order. Table 1 presents equally weighted averages of the 151,716 broker-stock-day observations.

The size of the top order for our sample averages \$59,807 and represents 0.48% of the average daily volume (ADV) in the stock during the month prior to our sample period (September 2016).[25] For mutual funds and pension funds that report to Abel Noser database, Hu et al. (2018) reports that an institutional ticket distributed across brokers averages \$96,495 in 2011, and that ticket size has been declining over the 2000 – 2011 period. The average percentage *quoted bid-ask (half) spread* at the time of order arrival is 19 bps, and ranges from 4 bps for large stocks to 52 bps for small stocks. Given this cross-sectional variation in liquidity, we present univariate results separately for small, medium and large stocks, and include stock fixed effects in the regressions. The average fill rate across broker-stock-days is 30.4%. Fill rates range from 22.6% for small stocks to 37.5% for large stocks. *Effective spread costs* are smaller than quoted spreads indicating that, on average, institutional orders do not aggressively seek liquidity. *Shortfall* is 7.1 bps. In the cross-section, small stocks are more expensive to trade than large stocks with *Shortfall* of 16 bps for small stocks and 3 bps for large stocks.

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 example, large wholesalers that purchase order flow fall in this category. Across all stocks, on the average broker-stock-

[25] Our conversations with market participants indicate that order sizes observed in OATS data are a fair representation of institutional flow. For example, IHS Markit reports that about 65% of institutional orders in April 2016 on its TCA platform were for less than \$200,000 (IHS Markit comment letter dated September 26, 2016, to the SEC on "Disclosure of Order Handling Information; Proposed Rule, Release No. 34-78309; File No. S7-14-16).

day, exchanges receive about 59% (55%) of the routes (routed quantity) and account for 78% (74%) of executions (executed quantity). ATSs receive 30% (33%) of the routes (routed quantity) but account for only 13% (17%) of executions (executed quantity). This result is consistent with the Tuttle (2012) finding that ATSs have lower fill rates than exchanges. We observe similar patterns across all stock categories.

3. Results

3.1 Affiliated ATS routing

Table 3 examines whether brokers route more orders to affiliated ATSs by comparing a broker to the sample benchmark. Specifically, for each broker-stock-day, we calculate the *%Affiliated ATS*, which is the proportion of routed quantity sent by the individual broker to an affiliated ATS. The benchmark for each stock-day is the proportion of total routed quantity sent by all brokers as a group to their respective affiliated ATSs. Next, we calculate the *average deviation* from the stock-day benchmark for a broker across all stock-days. We assign the broker's *average deviation* to each of their stock-day observations and then form terciles of broker-stock-days using the *average deviation* measure.[26] Importantly, each broker is assigned to a unique tercile, and by design, tercile 1 (T1) brokers route less, while tercile 3 (T3) brokers route more to affiliated ATSs venues, relative to the benchmark.

Table 3 describes venue choice for broker-stock-day observations in each tercile. Results in Table 3 indicate large differences in routing behavior across broker terciles. T1 and T2 brokers route 9% and 26% of shares to ATSs, with no affiliated ATS routing for T1 brokers and 6% for T2 brokers. T1 brokers route 73% of shares to exchanges, while T2 brokers route 60% to exchanges. Approximately 79% (73%) of the executed quantity for T1 (T2) brokers occurs on exchanges.

T3 brokers differ markedly from the other groups. T3 brokers route approximately 50% of shares to affiliated ATSs,[27] and 63% of shares to ATSs (affiliated and unaffiliated); however, only 17% of the executed quantity occurs on affiliated ATSs. Exchanges account for only 30% of T3 brokers' routed

[26] In the univariate analysis, the number of broker-stock-day observations in each tercile is approximately the same.
[27] The median T3 broker routes 47.5% of routed quantity to the affiliated ATS.

quantity but account for over 70% of executed quantity. A notable statistic is the 17% average execution share of affiliated ATSs for T3 brokers. During our sample period, the combined market share of all ATS venues is 14% and the market share of the largest ATS is only around 2%. Thus, T3 brokers route and execute more orders on affiliated ATSs and exhibit a large discrepancy between routing quantity and execution quantity on affiliated ATSs.

In panel B, we study whether the routing behavior of brokers to affiliated ATS venues is persistent. Given that our sample period is a single month, we form broker terciles based on *average deviation* in the first week of October 2016 and report retention statistics for future weeks, where retention rate is the percentage of brokers classified in the same tercile in future weeks. Results suggest that broker ranks based on affiliated ATS routing are highly persistent. In all future weeks, the affiliated ATS routing statistic increases from tercile 1 to tercile 3, T3 routing to affiliated ATSs remains at approximately 50%, and the T3 retention percentage exceeds 80%.

3.2 Execution quality: Univariate statistics

Table 4, panel A, presents average execution outcomes for broker terciles formed on affiliated ATS routing. A notable result is that average *fill rate* of top orders handled by T3 brokers is significantly smaller than those handled by T1 or T2 brokers. Specifically, the fill rate across broker-stock-days is 46% for T1 brokers, 28% for T2 brokers but only 17% for T3 brokers. The differences are not simply an artifact of brokers receiving orders in different stocks, as similar patterns exist for small, medium, and large stocks.

In the overall sample, the *effective spread costs* of T1 brokers is 1.1 bps, the corresponding statistics for T2 brokers and T3 brokers are 3.3 bps and 3.32 bps. T3 brokers have higher costs than do T1 brokers for medium and large stocks, while the differences are not statistically significant for small stocks. *Shortfall* is higher for T3 brokers than T1 and T2 brokers in the overall sample and in each stock category. In terms of magnitude, the average *Shortfall* for T3 brokers is 10.7 bps, which is significantly larger than the 4.2 bps for T1 brokers and 6.6 bps for T2 brokers. We find that the higher *Shortfall* of T3 brokers is attributable to higher *Delay*.

One potential explanation for higher trading costs is that clients send orders to T3 brokers when conditions are difficult. To understand differences in market conditions, we examine the percentage *quoted spread*s that prevail at the time of order arrival. The patterns observed in panels B to D present mixed evidence, reflecting more difficult conditions for some stock groups and easier conditions for other stock groups. These patterns highlight the need to assess execution quality differences after controlling for stock characteristics, order difficulty, and market conditions.

3.3 Regression analysis of execution quality

Table 5 examines the relation between affiliated ATS routing and order execution quality from a regression framework based on the following model:

$$Y_{i,s,t} = \beta_1 \% Affiliated\ ATS_{i,s,t} + \beta'\mathbf{X} + FE + \epsilon_{i,s,t}, \qquad (4)$$

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,* and *delay*. The variable of interest, %*Affiliated ATS*, is a continuous measure of the proportion of routed quantity to an affiliated ATS by broker *i* in stock *s* on day *t*. **X** is a vector of control variables including the log of broker-stock-day average broker order size, the average broker-stock-day arrival percentage quoted spread, stock-day average dollar depth at the best bid and ask, stock-day traded volume imbalance, the sum of squared 5-min mid-quote log returns (*RV*), and stock characteristic controls including the log of the stock price and log of the market capitalization for each stock-day.[28] Order size accounts for the well-established result that order difficulty increases with order size. Arrival-time spreads, depth, imbalance, and volatility account for variation in market conditions over time. Stock attributes, such as price and market cap, as well as stock fixed effects account for other important determinants of execution quality. Test statistics are based on standard errors clustered by stock and day.

Models 1 to 3 in Table 5 report specifications with the *fill rate* as the dependent variable. The negative coefficients for *%Affiliated ATS* indicate that brokers with higher affiliated ATS routing are

[28] Depth and Imbalance measures are sourced from WRDS intraday indicators. Imbalance is calculated as (Shares bought – share sold)/(Shares bought + shares sold).

associated with lower fill rates. In all specifications, *%Affiliated ATS* is highly significant at the 1% level. The stock fixed effects estimate (model 3) suggests that a one-standard-deviation increase in *%Affiliated ATS* is associated with an 11.6-percentage-point decline in fill rates. Thus, the T3 brokers' decisions to route more orders to affiliated ATSs is economically significant. The coefficients for the control variables are of the expected sign. For example, fill rates are positively associated with market capitalization and negatively associated with arrival spreads.

Effective spread costs do not show a significant association with brokers' affiliated ATS routing, indicating that a propensity to route to affiliated venues does not improve the execution prices received on the filled portion of a top order. On the other hand, brokers with high affiliated ATS routing are associated with larger *shortfall*. Based on model 3, a one-standard-deviation increase in *%Affiliated ATS* is associated with 1.8 bps larger *shortfall*. *Delay* shows similar patterns to *shortfall*, underscoring that the higher *shortfalls* stem from price drift and cleanup costs and not the prices received on executions.

3.4 Separating selection bias from broker conflicts

Ye and Zhu (2019) predict that large traders prefer ATSs when they have more information due to the higher opacity of such venues. Thus, T3 brokers' higher routing to ATSs may simply reflect a more informed clientele. Since informed orders are associated with higher trading costs, clients' information is potentially a source of selection bias, which could result in the lower execution quality associated with T3 brokers. When comparing model 1 to model 3 in Table 5, the shortfall coefficient for *%Affiliated ATS* declines from 6.91 to 5.84 with additional controls for stock and order attributes, which could potentially reflect such a bias. The OATS data do not include client identity, precluding the use of direct client-level controls. We present several approaches that account for the selection bias and attempt to isolate the impact of the brokers' routing decisions on execution quality.

3.4.1 Broker discretion.

As discussed earlier, brokers have more discretion in the handling of not-held orders than held orders. Greater discretion, in the presence of agency conflicts, is likely to be associated with more routing to affiliated venues. We examine whether execution quality is lower when T3 brokers have more discretion based on the following regression specification:

$$Y_{i,s,t} = \beta_1(NH \times T3) + \beta_2 T3 + \beta_3 NH + \beta'\mathbf{X} + FE + \epsilon_{i,s,t}, \qquad (5)$$

where $Y_{i,s,t}$ is the execution outcome for broker *i* in stock *s* on day *t*, separately for not-held and held orders. As above, execution quality is measured by *fill rates*, *effective spread costs*, *shortfall* and *delay*. The variable of interest, (*NH*×*T3*), interacts with the dummy variables *NH*, which equals one for not-held orders and zero for held orders, and *T3*, which equals one for T3 brokers and zero for non-T3 brokers. The interaction coefficient, which reflects the difference-in-differences (DID) estimate, compares the execution quality for not-held and held orders for T3 brokers relative to non-T3 brokers. **X** is a vector of control variables including the log of order size, arrival quoted spreads, depth, and average trade volume imbalance on the stock-day, as well as volatility. The estimation includes stock fixed effects. Test statistics are based on standard errors clustered by stock and day.

Table 6 summarizes the results. We find that fill rates are lower and execution costs are higher for not-held orders relative to held orders for T3 brokers versus the corresponding difference in execution outcomes for non-T3 brokers. Specifically, the DID estimate indicates that *shortfall* is 3.2 bps higher for not-held orders than held orders of T3 brokers relative to non-T3 brokers. We find no significant difference in *shortfall* between not-held and held orders of non-T3 brokers. Overall, the results point to lower execution quality when T3 brokers have more discretion but we note that this analysis could potentially underestimate the true effect of broker discretion. This is because clients typically seek guidance from brokers on execution strategies, which is likely to affect the execution instructions associated with held orders. We also recognize that the factors affecting the not-held and held orders usage may differ between the clients of T3- and non-T3 brokers. Below, we will provide additional tests aimed at separating the selection bias explanation from agency conflicts affecting execution quality.

3.4.2 Matched brokers based on ATS routing.

To control for the possibility that order difficulty is related to ATS routing, we implement a matched broker analysis where the broker-pairs exhibit a similar propensity to route orders to ATSs on the same stock-day. Specifically, using nearest-neighbor one-to-one propensity scores and a caliper of one quarter of a standard deviation, we obtain 42,208 matched broker-stock-days where average proportion of ATS routed quantity for T3 brokers is 51% and for non-T3 (control) brokers is 50%. Notably, while broker-pairs have a similar proportion of ATS routing on a stock-day, T3 brokers in matched-pairs predominantly route (42% of routed volume) to *affiliated* ATSs while non-T3 brokers in matched-pairs predominantly route (43% of routed volume) to *unaffiliated* ATSs. The matched analysis helps control for the client's preference for ATSs and isolates the impact of *affiliated* ATS routing on trading outcomes.

The matched broker analysis is based on the following specification:

$$Y_{i,s,t} = \beta_1 T3_{i,s,t} + \beta' \boldsymbol{X} + FE + \varepsilon_{i,s,t}, \qquad (6)$$

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 equals zero for control brokers. The vector of control variables, **X,** is limited to those that vary within a stock-day, including the log of the average order size on the broker-stock-day, and the average arrival-time percentage quoted spread on the broker-stock-day. Importantly, the specification includes matched-pair fixed effects, allowing $T3_{i,s,t}$ to capture differences between broker-pairs. 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 (5.4 percentage points) than for matched brokers. The *T3* coefficient in *Effective spread costs* regressions is negative and marginally significant, suggesting that T3 brokers obtain lower realized costs on the filled portion of an order. The *Shortfall* coefficient indicates higher costs (2.2 bps) for T3 brokers than matched non-T3 brokers. As before, higher shortfall costs are driven by higher *delay*. Our results indicate that brokers who route more orders to affiliated venues offer lower execution quality than other brokers who route similar quantity of orders to unaffiliated ATSs.

A further possibility is that the stock-days selected for matched analysis might disadvantage T3 brokers if non-T3 brokers use ATSs when market conditions are more favorable for ATS executions (e.g., Ready 2014). In a regression with stock fixed effects (unreported), we do not find a significant difference in volatility and trade imbalances between matched and unmatched days. Quoted spreads are weakly larger on matched days. Thus, it does not appear to be the case that the matched stock-days reflect easier conditions than unmatched stock days.

3.4.3 Determinants of venue choice.

Ready (2014) and Buti, Rindi, and Werner (2016) find that ATS execution market share is higher in more liquid stocks. These stocks are larger, with higher trading volume, lower bid-ask spreads, and smaller trade imbalances, indicating that ATS executions are more likely under easier market conditions. On the other hand, the model in Ye and Zhu (2019) predicts that clients prefer ATS venues for difficult orders. To the extent that order difficulty is associated with difficult conditions (e.g., one-sided imbalances), higher ATS usage is more likely when conditions are difficult. Further, it is possible that more informed clients cluster with T3 brokers.

In Table 8, we study the cross-sectional determinants of ATS executions and routes, in particular, whether we observe higher ATS usage by T3 brokers relative to non-T3 brokers when conditions are difficult. This analysis contributes to the prior literature that has focused on execution market share of ATS venues. All brokers' route and execution proportions are averaged across brokers for each stock-day. The dependent variable is either the proportion of quantity executed on ATSs (left subpanels) or the proportion of quantity routed to ATSs (right subpanels) on the stock-day. The model includes day fixed effects and, similar to Buti et al. (2016), firm size, volume, price, bid-ask spreads, depth, trade imbalance, and volatility as independent variables.

Table 8, panel A, presents the results for non-T3 brokers. All ATSs are included for non-T3 brokers. Results for executions are consistent with prior literature and show that ATS executions are more likely in liquid stocks characterized by larger size, higher volume, and greater depth. Non-T3 broker executions do not show a significant relationship with trade imbalances, and a positive relationship with stock volatility. Panel B summarizes the results for T3 brokers. We zero in on orders routed to affiliated ATSs; doing so allows us to separate broker conflicts from order difficulty. We find that T3-affiliated ATS executions are significantly more likely in easier conditions than non-T3 brokers' ATS executions.[29]

We find that the empirical determinants of ATS routing are markedly different than those of ATS executions. In panel A, consistent with Ye and Zhu (2019), non-T3 brokers are more likely to route orders to ATS venues under difficult conditions. In contrast, the results in panel B indicate that affiliated ATS routing by T3 brokers is largely insensitive to market conditions, namely, the coefficients for four of the seven variables are insignificant, while the volatility coefficient indicates ATS routing under easier conditions. Thus, it does not appear that informed investors choose T3 brokers to access affiliated ATS venues under difficult conditions. The insensitivity to market conditions in T3 brokers' affiliated ATS routing is consistent with the persistence in order routing shown in Table 3, panel B.

3.4.4 ATS characteristics.

In this section, we examine whether affiliated-ATSs exhibit design features that are consistent with greater opacity, which, all else equal, may be preferred by informed traders to limit leakage. We study individual Reg ATS-N filings and hand-collect available data on ATS characteristics that capture their respective trading environments. We create an ATS opacity measure based on one or zero scores for several characteristics that reasonably are associated with a less opaque venue: whether the ATS owner trades as a principal; whether the ATS allows proprietary trading firms (as concerns about leakage tend to center around such traders discerning their trading interest); whether the ATS transmits information out as IOIs to any outside entity; whether the ATS allows conditional orders, which allow a participant to receive notification of resting interest before deciding to "firm up"; whether the ATS allows IOC orders, which may make it easier to test the ATS for resting liquidity; whether the smart order router of the broker can see liquidity in the ATS; and whether ATS participants can see the book. We identify other characteristics associated with more opaque venues: whether opt-out provisions allow traders to restrict counterparties

[29] In unreported results, the coefficients for volume, spreads, depth, and imbalance are significantly larger in magnitude for T3 brokers than for non-T3 brokers at the 1% level and for size at the 5% level. Volatility coefficients do not show a significant difference.

(often related to principal flow but includes any counterparty restriction in our analysis); and whether the ATS is a block ATS. As expected, some characteristics are more common than others. To preserve venue anonymity, we construct an aggregate *Opacity score* that represents the sum of characteristics that make an ATS less opaque minus the sum of those that make an ATS more opaque (i.e., higher values reflect lower opacity).

This analysis is subject to several caveats: the ATS filings are from 2019, and the ATS features may have changed since our sample period; there is some subjectivity in the characteristics we focus on; and, while we treat each characteristic equally, some are likely to be more important than others. With these caveats in mind, the average *Opacity score* for T3-affiliated-ATSs is 2.60, and the average score for non-T3 ATSs is 2.13. Thus, T3 brokers' affiliated ATSs do not appear to offer design features that are particularly different than other ATSs in mitigating leakage and, therefore, attracting informed investors to T3 brokers.

3.4.5 Matched order horse races.

We further account for differences in order attributes, such as price aggressiveness and order instructions, as well as market conditions and client intent at the time of order submission, by adapting the paired route "horse race" approach developed by Sofianos, Xiang, and Yousefi (2010) and Battalio, Corwin, and Jennings (2016) to our empirical setting. Specifically, we pair individual, child routes made by T3 brokers to affiliated ATSs with other identically priced, concurrent routes to unaffiliated ATSs. The pairs are matched separately for two common order types: midpoint peg orders and primary peg orders. Midpoint peg orders are limit orders where the limit price dynamically updates to equal the midpoint of prevailing NBBO, while primary pegs are dynamically tied to the passive side of the NBBO.[30] We require that (a) the matched orders be open at the same time, (b) the first order in the pair must be active, unmodified, and not have received any fills when the second order in the pair is routed, (c) one of the matched orders receives

[30] Pegged orders are common on ATSs, with midpoint pegs as the most widely observed order pricing condition code. In comparison, static price limit orders are rare.

a partial or complete fill, while its paired order is active, unmodified, and has not received any fills, and (d) matched pegged orders arrive during the same NBBO price state. The paired child orders are open at the same time, which controls for market conditions, and arrive in the same NBBO price state with the same instructions, which accounts for client intent and the type of ATS venue. The winner of the horse race is the order that obtains the first fill, while both orders are active and unmodified. Should both orders obtain fills, an order wins if it obtains its first fill at least 500 ms before its pair. If both orders obtain their first fills within 500 ms of one another, the horse race is declared a tie.

We obtain 1,464,349 matched pairs for midpoint peg orders and 747,642 matched pair for passive pegs. Table 9, panel A, presents the results for midpoint peg (child) orders. The fill rate (calculated as executed quantity divided by child order quantity) for T3 brokers' affiliated ATS routes is 41.1%, which is significantly lower than the 50% fill rate for matched unaffiliated ATS routes.[31] Unaffiliated ATS routes are filled earlier 53% of the time, T3-affiliated ATS routes are filled earlier 42% of the time and ties are observed about 5% of the time.[32] We also examine "good fill ratios," which measure price movements after the execution of a route. If price moves are favorable for the order (e.g., stock price rises after the execution of a buy limit order) then the order is marked as a good fill.[33] The results show no significant differences in good fill ratios. Table 9, panel B, presents a similar analysis for primary peg orders with similar results; unaffiliated ATS routes have higher fill rates and are more likely to win the horse races.

In summary, both order types show that unaffiliated ATS routes experience better execution outcomes than T3-affiliated ATS routes, after controlling for order instructions, market conditions and

[31] Higher fill rates in this analysis reflect our condition that at least one of the paired routes receive an execution. This characteristic of horse races also can be seen in Battalio, Corwin, and Jennings (2016) and Battalio, Griffith, and Van Ness (forthcoming).

[32] ATS routes can specify a minimum quantity to be filled, a condition that can affect outcomes. We repeat the matched analysis after removing routes that have a "minimum quantity" instruction. The results yield similar inferences.

[33] We follow Battalio, Griffith, and Van Ness (forthcoming) in using a 5-min horizon after an execution. Good fill ratios are more useful in evaluating static limit order execution quality, since they directly address concerns related to limit order traders being picked off by faster traders as market prices move against limit orders. Our analysis of pegged orders makes the measure less useful. However, a concern remains because of the practice of latency arbitrage if an ATS pegs its price to the slower-moving NBBO than the direct exchange feeds. In that scenario, a lower good fill ratio would weigh against the higher fill rates. Along similar lines, given that the matched pairs are pegged orders and meet strict selection criteria, shortfall cost measures are less useful in assessing execution quality and further makes comparison with other analyses less meaningful.

client intent. Establishing similar results for both order types separately has the additional advantage that it accounts for the possibility of a specific design feature systematically varying between T3-affiliated ATSs and other ATSs: whether an ATS skews more toward midpoint or at-the-quote matching. These results point to a potential mechanism that may explain the execution quality differences observed in the broader sample.

3.4.6 Tick Size Pilot analysis.

We examine changes in broker routing practices and execution quality outcomes surrounding the SEC's implementation of the Tick Size Pilot (TSP) program in October 2016. One of the intended effects of this regulatory experiment was to significantly reduce executions at ATSs that match orders at the quotes for a subset of stocks, which in turn could affect execution quality. Specifically, the trade-at prohibition for randomly assigned group 3 (G3) stocks makes it difficult for ATSs to execute trades at the best quoted prices (i.e., without offering significant price improvement). Notably, the TSP still allows midpoint executions for G3 stocks. Thus, venues with more midpoint executions are less affected by the TSP.

Accordingly, we focus this analysis on T3 brokers with affiliated ATSs that have a proportion of executions at the NBBO midpoint that is at or below the ATS-level median during the pre-TSP period (September 2016). We use two control samples in our analysis: the control stocks specified by the TSP, which are unaffected by all TSP rules, and treatment group 2 (G2) stocks, which differ from group 3 stocks only in the implementation of the trade-at rule. T3 brokers are matched with non-T3 brokers based on the broker-stock-day average proportion of routed quantity sent to ATSs during the pre-TSP period. As expected, T3 brokers have higher ATS routing; in both the G3-Control comparison sample, and the G3-G2 sample, T3 brokers route approximately 66% of routed quantity to ATSs, while the matched brokers route approximately 59%.

We test the following competing hypotheses: if T3-affiliated ATS routing is associated with optimal routing, then, relative to non-T3 brokers, T3 brokers' execution outcomes will *worsen* when venue choice is constrained. On the other hand, the TSP may help resolve agency conflicts by making some ATSs less viable, implying T3 brokers' execution outcomes will *improve* relative to non-T3 brokers. The analysis is a triple difference-in-differences comparing T3 versus non-T3 brokers, in G3 versus control stocks, in the period before and after TSP implementation. We estimate the following equation:

$$Y_{i,s,t} = \beta_1 G3_{i,s,t} + \beta_2 T3_{i,s,t} + \beta_3 Post_{i,s,t} + \beta_4 (G3_{i,s,t} \times T3_{i,s,t}) + \beta_5 (Post_{i,s,t} \times G3_{i,s,t}) + + \beta_6 (Post_{i,s,t} \times T3_{i,s,t}) + \beta_7 (G3_{i,s,t} \times Post_{i,s,t} \times T3_{i,s,t}) + \beta' \boldsymbol{X} + \varepsilon_{i,s,t}, \quad (7)$$

where $G3_{i,s,t}$ is an indicator variable that equals one for treatment group 3 stocks and zero otherwise, $T3_{i,s,t}$ is an indicator variable that equals one for T3 brokers, and zero otherwise. $Post_{i,s,t}$ is an indicator variable that equals one for November 2016 and zero for September 2016. **X** is a vector of control variables including the log of broker-stock-day average order size, stock-day trade volume imbalance, the stock-day sum of squared 5-min mid-quote log returns (RV), the daily VIX index, and stock attributes that include the log of the average stock price and log of the average market capitalization during September 2016. Test statistics are based on standard errors clustered by stock and day.

Table 10 presents the results. Panel A presents results relative to TSP control stocks, and panel B relative to G2 stocks. The variable of interest is *Post×G3×T3*, which captures the incremental difference in differences for T3 brokers relative to non-T3 brokers. Panel A shows that T3 brokers' ATS routed quantity shows a relative decline, *Fill rate* increases and *Shortfall* and *Delay* both decline. Thus, our results are consistent with the agency conflicts hypothesis, wherein T3 brokers are associated with relative improvement in execution outcomes after TSP program is implemented.[34] Panel B shows similar results with G2 stocks as the control sample. While the TSP analysis is subject to the caveat that the program was designed for smaller stocks, two advantages are noteworthy. First, the TSP program provides an exogenous constraint to the broker routing decision that allows a test of the agency conflicts hypothesis. Second, the

[34] In Internet Appendix Table A5, we include this analysis across all ATSs (i.e., including midpoint ATSs). The results point in the same direction but are weaker.

TSP sample provides a useful out-of-sample analysis, as the tercile classifications of brokers is based on the main sample in October 2016.[35]

3.4.7 Robustness analysis.

We briefly describe three robustness tests. First, we examine whether trading outcomes are similar for larger institutional orders. In Internet Appendix Table A3, we separately examine large orders defined as those that are equal to or greater than the 99th percentile of top order size for a stock in our sample. The average order size for these 3.2 million large orders is $581,691 ranging from $926,053 for large stocks to $85,806 for small stocks. These orders represent 2.08% of average daily traded volume in the average stock, ranging from 0.73% for large stocks to 7.48% for small stocks. The results for large orders broadly mimic those for the overall sample. Second, in Internet Appendix Table A4, we show that the results are similar when we include a measure of order-level information borrowed from prior literature that compares order arrival time NBBO midpoint to future NBBO midpoints at 5 min, 2 days, and 20 days.

Third, we implement an alternate methodology to classify brokers that considers the ATS market share, thus accounting for brokers who operate large versus small ATSs. Absent agency conflicts, larger ATSs are more likely to receive orders from an affiliated broker. To account for ATS market share, brokers are placed into terciles based on the difference between the proportion of routed quantity sent by a broker to its affiliated ATS relative to the proportion of routed quantity sent by all brokers to the same ATS (that is, the ATS's routing market share in our sample). We find that the T3 brokers identified by this methodology are identical to the T3 brokers identified in our main analysis.

4. Discussion and Conclusions

We find that brokers who route more orders to affiliated ATSs are associated with lower execution quality for their customers. How does the economic significance of this broker conflict compare with other

[35] The *T3* coefficient, alone, compares T3 and non-T3 brokers in control samples in September 2016. Results are similar to our main findings. In Internet Appendix Table A6, we use a specification with broker, stock, and day fixed effects; results are qualitatively similar.

broker conflicts studied in the literature? Because Battalio, Corwin, and Jennings (2016) focus on nonmarketable retail orders, their sample is not comparable to ours. Two industry studies, Sofianos, Xiang, and Yousefi (2011) and Bacidore, Otero, and Vasa (2011), examine venue fee conflicts for institutional orders. For nonmarketable orders, both studies find that the routing logic that increases fill rates leads to lower costs. These studies estimate cost differentials in the range of 0.4 to 0.9 bps for large and small stocks. From the matched broker analysis in Table 7, we note that a conservative estimate of shortfall differences attributable to T3 brokers' routing is 2.2 bps. The numbers are not directly comparable: the differences in Bacidore, Otero, and Vasa (2011) are for nonmarketable, child orders only, while our study includes all order types arising from handling of top orders; and the venue fee examinations in the two studies center on child orders, while we examine broker-level top orders, where shortfall costs are larger. With these challenges in mind, it appears that the agency conflict we document is of a similar order of magnitude to the conflict related to venue fees.

Conrad, Johnson, and Wahal (2001) estimate cost differences of 15 and 18 bps for buyer and seller-initiated trades associated with conflicts due to soft dollar payments. These estimates are significantly larger than the estimates of our study, or the conflict related to venue fees. Direct comparisons are difficult because of differences in the sample and the time periods studied. Specifically, the sample period examined by Conrad et al. (2001) ends in 1996; their average implicit institutional trading costs of 47 bps are significantly higher than the 25 bps reported by Anand et al. (2012) over the 1999-2008 period, and the 23 bps reported by ITG, Inc., in Q2 2017. With the decline in overall institutional trading costs, it is likely that the cost differential attributable to soft dollars has declined in recent years. Further, Conrad et al. (2001) study institution-level parent orders, while we study institution-broker-level orders, implying the trading costs for our sample are likely to be smaller. With these caveats in mind, the magnitudes associated with soft dollars are likely to be larger, since these arrangements obscure the focus on execution quality and encompass other issues related to agency conflicts (including those related to own-ATS routing and venue fees) and poor performance.

Institutional traders are sophisticated market participants. Why then do we still see persistent and meaningful differences in execution quality across brokers? There are several frictions in monitoring brokers that in aggregate may provide an answer. Some institutions are relatively insensitive to execution cost differences.[36] Some institutions rely on brokers not only for data but also for data analysis.[37] The data made available by brokers are frequently limited to executions. Broker routing data may not be comparable across brokers, or easy to interpret.[38] Finally, institutions tend to concentrate order flow with a small number of brokers (Goldstein et al. 2009), making comparisons across brokers difficult and limiting the institution's view into industrywide practices.

Even where institutions detect issues with broker execution quality, the relationship can be deeply embedded (as Goldstein et al. [2009] note, brokers can be selected for reasons other than execution quality, such as research reports, IPO allocations, access to corporate executives, and conferences), and the typical resolution is to negotiate with the broker rather than replace them.[39] Consistent with persistent relationships, Anand et al. (2012) find that the loss of market share for poorly performing brokers is economically small. Even so, brokers are sensitive to maintaining and growing their relationships with clients. Overall, increased attention on order handling practices is likely to tilt the balance toward reduced broker agency conflicts.[40]

[36] Babelfish Analytics (2018) highlights the variation in attention to execution cost and routing analytics, "Unfortunately, most firms do not perform routing analysis on a regular basis and consequently bear the burden of these costs…."

[37] The SEC (2016) outlines the challenges institutions (especially small institutions) face in obtaining comparable data from different brokers. Cronin (2012) notes the heterogeneity in institutions' ability to get data from brokers.

[38] For example, Connor, Clark, and Lunn (2014) note that the concentration of executions in brokers' own ATSs raises questions about routing practices but isn't able to examine routing or execution quality effects of such routing. Southeastern Asset Management (2010) notes that, "enormous complexity introduced by this process has clouded order handling to the point where even educated customers are never completely confident how or why their orders are routed to specific venues in a specific way." Blackrock (2014) makes a similar point in, "Although market participants are still capable of monitoring execution quality, the investment and resources required to do so effectively make it difficult for all but the largest investors." Investment Companies Institute (2010) notes the need for better disclosure from brokers, specifically pertaining to routing.

[39] Markit (2016) and Investment Companies Institute (2014) note that enhanced routing disclosure will allow investors to enter into better dialogue with their brokers. The routing analysis firm, Babelfish Analytics, states its goal as to, "… help investors work with their brokers."

[40] We are unable to answer the question of why all brokers do not operate ATSs or route more to their existing ATSs, similar to T3 brokers. A possibility exists that brokers who expect their ATSs to be less successful conclude that the delay costs associated with ATS routing may be untenably high. That is, they consider the trade-offs, between private benefits, on the one hand, and the effects on client relationships and the additional regulatory obligations associated

Market participants agree on the benefits of consistent and detailed information on order handling. Recent initiatives on better disclosure on order handling practices have come from both the industry and regulators. Industry initiatives include templates for brokers to provide information across all their clients on how their orders are handled.[41] In recent years, financial regulators, including the Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA), have named best execution among their annual regulatory priorities.[42] The recently implemented Rule 606(b)(3) by the SEC marks a significant step forward in the analysis of brokers handling of institutional orders. The rule requires brokers to provide (upon request) detailed reports to institutions on how their not-held orders are routed.

Rule 606(b)(3) enhances the current disclosure regime by standardizing the information in these broker reports. As SEC (2018) notes, institutions can combine the broker reports with other transaction cost tools to relate brokers' routing decisions to implementation shortfall costs. The type of analysis conceived in the SEC release is similar to the analysis in our study, except that Rule 606(b)(3) would limit the data available to institutions to their own orders. For institutions that deal with multiple brokers, Rule 606 can yield rich insights on broker's order routing decisions and the impact on trading costs.

The widespread support from the industry to the Rule 606 revision proposal indicates both the need for routing data and an eagerness to tackle routing related issues. We expect buyside traders to be better engaged with brokers in light of the higher visibility afforded by the new Rule 606. We also believe that there is room for further initiatives. Standardized public disclosures are difficult to establish because of the heterogeneity in client types and the intellectual property concerns of both clients and brokers. However, buy-side and sell-side institutions can support initiatives to create central repositories of data that

with ATS usage, on the other hand, differently than T3 brokers. Absent detailed data on internal processes and costs, it is difficult to pin down the causes of the cross-sectional variation in ATS ownership and usage across brokers.

[41] See, for example, a template resulting from a transparency group organized by the Investment Companies Institute, the Managed Funds Association and SIFMA (https://www.sifma.org/wp-content/uploads/2017/05/sifma-ici-and-mfa-writes-letter-to-sec-on-regulation-nms-prepares-order-routing-disclosure-template.pdf). The Financial Information Forum (https://www.sec.gov/comments/s7-14-16/s71416-35.pdf), and the Healthy Market Initiative (https://healthymarkets.org/initiatives/order-routing-transparency) provide useful templates for participants.

[42] See, for example, FINRA's 2019 and 2020 Annual Priorities letters at https://www.finra.org/rules-guidance/communications-firms/2019-annual-risk-monitoring-and-examination-priorities-letter and https://www.finra.org/rules-guidance/communications-firms/2020-risk-monitoring-and-examination-priorities-letter).

researchers can access to provide industrywide analyses, while preserving the anonymity of clients, brokers and strategies.

References

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman. 2012. Performance of institutional trading desks: An analysis of persistence in trading costs. *Review of Financial Studies* 25:557–98.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman. 2013. Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis. *Journal of Financial Economics* 108:773–97.

Anand, A., and D. Weaver. 2004. Can order exposure be mandated? *Journal of Financial Markets* 7: 405–26.

Babelfish. 2018. Comment letter Re: Transaction Fee Pilot (File No: S7-05-18).

Bacidore, J., H. Otero, and A. Vasa 2011. Does Smart Routing Matter? *Journal of Trading* 6:32–37.

Battalio, R. 1997. Third market broker-dealers: cost competitors or cream skimmers? *Journal of Finance* 52:241–52.

Battalio, R., T. Griffith, and R. Van Ness. Forthcoming. Do (should) brokers route standing limit orders seeking to trade US equity options to wholesalers? *Journal of Financial and Quantitative Analysis*.

Battalio, R., S. Corwin, and R. Jennings. 2016. Can brokers have it all? On the relation between make-take fees and limit order execution quality. *Journal of Finance* 71:2193–238.

Battalio, R., J. Greene, B. Hatch, and R. Jennings. 2002. Does the limit order routing decision matter? *Review of Financial Studies* 15:159–94.

Battalio, R., B. Hatch, and M. Saglam. 2018. The cost of routing orders to high frequency traders. Working Paper, University of Notre Dame.

Bessembinder, H., M. Panayides, and K. Venkataraman. 2009. Hidden liquidity: An analysis of order exposure strategies in electronic stock markets. *Journal of Financial Economics* 94:361–83.

Blackrock. 2014. Comment letter RE: Equity Market Structure Recommendations; Concept Release on Equity Market Structure, File No. S7-02-10; Regulation Systems Compliance and Integrity, File No. S7-01-13; and Equity Market Structure Review. September 12, 2014.

Blackrock. 2016. Comment letter Re: Disclosure of Order Handling Information (File No. S7-14-16). September 26, 2016.

Bloomberg. 2016. Comment letter Re: Disclosure of Order Handling Information (RIN 3235-Al67); Notice of Proposed Rulemaking (Release No. 34-78309; File No. S7-14-16). September 26, 2016.

Bloomfield, R., M. O'Hara, and G. Saar. 2015. Hidden liquidity: Some new light on dark trading. *Journal of Finance* 70:2227–76.

Boehmer, E., D. Li, and G. Saar. 2018. The competitive landscape of high-frequency trading firms. *Review of Financial Studies* 31:2227–76.

Brogaard, J., B. Hagstromer, L. Norden, and R. Riordan. 2015. Trading fast and slow: Colocation and market quality. *Review of Financial Studies* 28:3407–43.

Brogaard, J., T. Hendershott, and R. Riordan. 2014. High-frequency trading and price discovery. *Review of Financial Studies* 27:2267–306.

Busse, J.A., T. Chordia, L. Jiang, and Y. Tang. 2020. Transaction costs, portfolio characteristics, and mutual fund performance. *Management Science* Advance Access published July 16, 2020, 10.1287/mnsc.2019.3524.

Buti S., B. Rindi, and I. Werner. 2017. Dark pool trading strategies, market quality and welfare. *Journal of Financial Economics* 124:244–65.

Buti S., B. Rindi, and I. Werner. 2016. Diving into dark pools. Working Paper, Université Paris-Dauphine.

Capital Group. 2016. Comment letter RE: Disclosure of Order Handling Information – Proposed Rule File No. S7-14-16. September 30, 2016.

Card, D., R. Chetty, M. Feldstein, and E. Saez. 2010. Expanding access to administrative data for research in the United States. White Paper.

Connor, Clark, Lunn. 2014. Comment letter Re: Comments in Response to Application for Recognition of Aequitas Innovations Inc. and Aequitas Neo Exchange Inc. As an Exchange. September 11, 2014.

Conrad, J., K. Johnson, and S. Wahal. 2001. Institutional trading and soft dollars. *Journal of Finance* 56:397–416.

Cronin, K. 2012. Testimony of Kevin Cronin, Global Head of Equity Trading, Invesco on Behalf of the Investment Company Institute, Subcommittee on Capital Markets and Government Sponsored Enterprises, Committee on Financial Services, U.S. House of Representatives.

Degryse, H., M. Van Achter, and G. Wuyts. 2009. Dynamic order submission strategies with competition between a dealer market and a crossing network. *Journal of Financial Economics* 91:319–38.

Einav, L., and J. Levin. 2014. Economics in the age of big data. *Science* 346:1243089.

Easley, D., N. Kiefer, and M. O'Hara. 1996. Cream-skimming or profit-sharing? The curious role of purchased order flow. *Journal of Finance* 51:811–33.

Fidelity. 2016. Comment letter Re: Disclosure of Order Handling Information; File No. S7-14-16. September 26, 2016.

Financial Information Forum. 2016. Comment letter Re: Release No. 34-78309; File No. S7-14-16; Disclosure of Order Handling Information. November 7, 2016.

Goldstein, M., P. Irvine, E. Kandel, and Z. Weiner. 2009. Brokerage commissions and institutional trading patterns. *Review of Financial Studies* 22:5175–212.

Griffin, J., J. Harris, T. Shu, and S. Topaloglu. 2011. Who drove and burst the tech bubble? *Journal of Finance* 66:1251–90.

Handa, P., and R. Schwartz. 1996. Limit order trading. *Journal of Finance* 51:1835–61.

Harris, L., and J. Hasbrouck. 1996. Market vs. limit orders: The SuperDOT evidence on order submission strategy. *Journal of Financial and Quantitative analysis* 31:213–31.

Hasbrouck, J., and G. Saar. 2002. Limit orders and volatility in a hybrid market: The island ECN. Working Paper, New York University.

Hendershott, T., and H. Mendelson. 2000. Crossing networks and dealer markets: Competition and performance. *Journal of Finance* 55:2071–115.

Hendershott, T., C. Jones, and A. Menkveld. 2011. Does algorithmic trading improve liquidity? *Journal of Finance* 66:1–33.

Hu, G., K. Jo, Y. Wang, and J. Xie. 2018. Institutional Trading and Abel Noser Data. *Journal of Corporate Finance* 52:143–67.

Investment Companies Institute. 2010. Comment letter Re: Concept Release on Equity Market Structure (File No. S7-02-10). April 21, 2010.

———. 2014. Comment letter Re: Customer-Specific Order Routing Disclosures for Institutional Investors. October 23, 2014.

IOSCO. 2017. Order routing incentives, Final Report, FR08/2017.

Keim, D., and A. Madhavan. 1997. Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. *Journal of Financial Economics* 46:265–92.

Kirilenko, A., A. Kyle, M. Samadi, and T. Tuzun. 2017. The flash crash: High-frequency trading in an electronic market. *Journal of Finance* 72:967–98.

Korajczyk, R., and D. Murphy. 2019. High-frequency market making to large institutional trades. *Review of Financial Studies* 32:1034–67.

Kyle, A. 1985. Continuous auctions and insider trading. *Econometrica* 53:1315–36.

Markit. 2016. Comment letter Re: Disclosure of Order Handling Information; Proposed Rule, Release No. 34-78309; File No. S7-14-16. September 26, 2016.

Menkveld, A., B. Yueshen and H. Zhu. 2017. Shades of darkness: A pecking order of trading venues. *Journal of Financial Economics* 124:503–34.

NY Attorney General. 2014. Attorney General of the State of New York, Plaintiff, against Barclays Capital, Inc., and Barclays PLC, Index No.: 451391/2014, Supreme Court of the State of New York County of New York.

Perold, A. 1988. The implementation shortfall: Paper versus reality. *Journal of Portfolio Management* 14:4–9.

Puckett, A., and X. Yan. 2011. The interim trading skills of institutional investors. *Journal of Finance* 66:601–33.

Ready, M. 2014. Determinants of volume in dark pool crossing networks. Working Paper, University of Wisconsin-Madison.

Reed, A., M. Samadi, and J. Sokobin. 2020. Shorting in broad daylight: Short sales and venue choice. *Journal of Financial and Quantitative Analysis* 55:2246–69.

Saglam, M. Forthcoming. Order anticipation around predictable trades. *Financial Management*.

SEC. 2016. Disclosure of order handling information. Securities Exchange Act Release No. 78309 (July 13, 2016), 81 FR 49432, 49434 (July 27, 2016).

———. 2018. Disclosure of order handling information. Securities Exchange Act Release No. 34-84528.

Sofianos, G., J. Xiang, and A. Yousefi. 2011. All-in shortfall and optimal order placement. *Street Smart* 42:January 2011.

———. 2010. Smart routing goes to the races: Venue toxicity comparisons. *Street Smart* 41:December 2010.

Southeastern Asset Management. 2010. Comment letter Re: Concept Release on Equity Market Structure (File No: S7-02-10), April 28, 2010.

Tuttle, L. 2013. Alternative trading systems: Description of ATS trading in national market system stocks. Working Paper, Securities and Exchange Commission.

van Kervel, V., and A. Menkveld. 2019. High-Frequency Trading around Institutional Orders. *Journal of Finance* 74: 1091-1137.

Wagner, W. 1993. Defining and measuring trading costs. In *execution techniques, true trading costs, and the microstructure of markets*, ed. K. Sherrerd. Charlottesville, VA: Association for Investment Management and Research.

Wagner, W., and M. Edwards. 1993. Best execution. *Financial Analysts Journal* January:65–71.

Werner, I. 2003. Execution quality for institutional orders routed to NASDAQ dealers before and after decimals. Working Paper, Ohio State University.

White, M. J. 2016. Keynote Address Investment Company Institute 2016 General Meeting – "The Future of Investment Company Regulation". Speech, Washington, DC. https://www.sec.gov/news/speech/white-speech-keynote-address-ici-052016.html

Yang, L., and H. Zhu. 2020. Back-running: Seeking and hiding fundamental information in order flows. *Review of Financial Studies* 33:1484–533.

Ye, M. 2011. A glimpse into the dark: Price formation, transaction cost and market share of the crossing network. Working Paper, University of Illinois at Urbana-Champaign.

Ye, M., and W. Zhu. 2019. Strategic informed trading and dark pools. Working Paper, University of Illinois at Urbana-Champaign.

Zhu, H. 2014. Do dark pools harm price discovery? *Review of Financial Studies* 27:747–89.

Appendix:

Sample Construction

We identify institutional orders handled by institutional brokers based on a combination of broker classifications from Griffin et al. (2011) and the beneficiary owner field in the OATS data. The beneficiary owner field is marked as institutional, individual, combined, employee, market maker, or proprietary flow, and in many cases, unknown or null.[43]

The sample of brokers consists of the following: (a) brokers identified by Griffin et al. (2011) as "Institutional" or "Largest Ibanks," (b) brokers classified by Griffin et al. (2011) as "Mixed," where at least 40% of the orders with a known beneficiary type are marked as institutional, and (c) brokers not classified by Griffin et al. (2011) with at least 40% of the orders with a known beneficiary type and at least 40% of the orders with a known type are marked as institutional.

We examine top orders that originate with a broker; that is, we exclude orders that are routed to an institutional broker from another broker (e.g., an introducing broker). This filter allows us to focus on order flow where the broker has a direct relationship with the institutional client and avoids any confounding issues due to the arrangements between brokers. Consistent with Griffin et al. (2011), we examine all orders placed with a broker. We consider additional choices in creating a sample: (a) including only orders marked as institutional, (b) including orders marked as institutional and null/unknown, or (c) creating a hybrid approach where, for some brokers, the sample includes only institutional orders and for others institutional and unknown.[44] In Internet Appendix Table A7, we show that results are qualitatively similar if the sample is based on the other three approaches.

[43] 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.

[44] In the initial version of the paper, we examine a sample constructed using the hybrid approach (i.e., approach (c)). We subsequently modified the sample to include all orders placed with the broker to address concerns about the subjective decisions in creating the hybrid sample. A prior version (dated May 15, 2019) of the study reported the results using all the orders placed with the broker but the Appendix incorrectly described the sample as being hybrid.

To ensure that we focus on active brokers, we require that the number of top orders received by the broker in October 2016 that survive the filters imposed above exceed 10,000. 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 50% or higher of their routed order flow from other brokers; and well-known proprietary firms and market makers.

The sample of stocks consists of a size-stratified group of 300 stocks traded in October 2016. To construct the sample, we retain U.S. listed common shares with a share price of at least five dollars using CRSP data at the end of December 2015. For this group of stocks, we form decile portfolios based on market capitalization in December 2015 and select the 30 largest stocks from each decile that are available on the October 2016 TAQ Master Files (based on a CUSIP merge between CRSP and TAQ) and OATS database (based on a CUSIP merge between TAQ and OATS).

We impose several additional data filters:

- We remove orders received outside of trading hours.
- We remove orders with more than one top order assigned to the life cycle. 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 orders for which the order arrival bid or offer is less than $1.
- We remove orders that were received but are not associated with any routes by the broker.
- We remove orders with life cycle 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%. Fill rates can exceed 100% if the order size is increased during the order's life cycle.
- We remove orders whose time to execution or time to route is less than -2 s 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," and "W," remove canceled quotes, remove quotes without an associated price or positive share quantity. We remove quotes corresponding to locked and crossed markets and percentage bid-ask spreads larger than 5%.

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 these order handling codes for each broker used in the horse races take place at the midpoint of the NBBO. We use the order handling code "FR" to identify primary pegged orders. We verify that at least 70% of executions for this order handling code for each broker used in the horse races take place at the passive quote of the NBBO.

For the tick size pilot, we examine stocks classified as control stocks during the initial rollout of the pilot as they were not subject to a modification event during the program (i.e., merger and acquisition, delisting, or ticker change); doing so results in 940 stocks. We examine the October 10, 2016, and October 17, 2016, cohorts for treatment group 2 stocks, and the October 24, 2016, and October 31, 2016, cohorts for treatment group 3 stocks, which were not subject to a modification event during the program and were "rolled back" at the conclusion of the pilot, resulting in 299 stocks for treatment group 2 and 292 stocks for treatment group 3. We merge with CRSP and remove non-U.S.-listed common stocks, resulting in 250 G3 stocks, 257 G2 stocks and 820 control stocks. For these stocks, we examine OATS order data for our sample of 43 brokers, applying the additional filters discussed for the main sample. We remove stock-days with less than 20 trades and trading on November 25, 2016, due to an early market closure. The final sample consists of 247 G3 stocks, 257 G2 stocks, and 811 control stocks.

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 (%ADV)* is the average order size as a percentage of average daily volume in the stock in September 2016. *Order size ($)* is the average dollar order size. *Rt qty/order qty* is the ratio of number of shares routed during the orders life cycle 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* 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. *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order. *Shortfall* 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.

	#Brokers	#Obs	#Orders (mm)	Order size (%ADV)	Order size ($)	Rt qty/ order qty
All stocks	43	151,716	358.43	0.48%	$59,807	9.99
Large stocks	43	60,551	268.90	0.09%	$110,050	5.62
Medium stocks	43	60,747	74.84	0.37%	$34,706	9.22
Small stocks	40	30,418	14.70	1.49%	$9,920	20.20

	Fill rate	Arrival spread (bp)	Eff. spread (bp)	Delay (bp)	Shortfall (bp)
All stocks	30.35%	18.60	2.58	6.56	7.10
Large stocks	37.47%	3.98	1.30	2.91	3.09
Medium stocks	27.15%	16.49	2.21	6.29	6.64
Small stocks	22.58%	51.92	6.61	14.36	16.02

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.

	A: Routes			*B: Executions*		
	ATS	Exchange	Firm	ATS	Exchange	Firm
All stocks	29.54%	58.81%	11.66%	13.29%	77.79%	8.91%
Large stocks	26.69%	58.81%	14.50%	12.67%	76.52%	10.81%
Medium stocks	30.48%	58.80%	10.72%	14.31%	77.59%	8.10%
Small stocks	33.32%	58.80%	7.89%	12.47%	81.43%	6.10%

	C: Routed qty			*D: Executed qty*		
	ATS	Exchange	Firm	ATS	Exchange	Firm
All stocks	32.52%	54.82%	12.67%	16.56%	73.90%	9.54%
Large stocks	30.63%	53.44%	15.93%	16.56%	71.97%	11.46%
Medium stocks	33.17%	55.24%	11.59%	17.45%	73.87%	8.68%
Small stocks	34.96%	56.70%	8.33%	14.47%	78.70%	6.83%

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 life cycle to its top order quantity. 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. 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 3 weeks. *Retention %* is the percentage of brokers that remain in the same tercile in the future week. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

A: Venue choice statistics by broker tercile

		Rt qty	%ATS		%Affiliated ATS	
Broker tercile	#Obs	/order qty	Rt qty	Ex qty	Rt qty	Ex qty
T1 (least %affiliated ATS)	51,535	4.28	9.40	5.31	0.00	0.00
T2	50,949	9.72	25.97	17.21	6.42	4.99
T3 (most %affiliated ATS)	49,232	16.23	63.49	27.13	49.85	16.65
T1-T3			-54.09^{***}	-21.82^{***}	-49.85^{***}	-16.65^{***}
T2-T3			-37.52^{***}	-9.92^{***}	-43.43^{***}	-11.66^{***}

	%Unaffiliated ATS		%Exchange		%Firm	
Broker tercile	Rt qty	Ex qty	Rt qty	Ex qty	Rt qty	Ex qty
T1 (least %affiliated ATS)	9.39	5.31	72.66	78.96	17.94	15.73
T2	19.55	12.22	60.48	72.49	13.55	10.30
T3 (most %affiliated ATS)	13.64	10.48	30.27	70.24	6.24	2.62
T1-T3	-4.25^{***}	-5.17^{***}	42.39^{***}	8.72^{***}	11.71^{***}	13.10^{***}
T2-T3	5.90^{***}	1.74^{***}	30.21^{***}	2.25^{***}	7.31^{***}	7.68^{***}

B: Persistence in venue choice

	Week			
Broker tercile	Week T	Week $T+1$	Week $T+2$	Week $T+3$
T1 %affiliated ATS	0.00	0.00	0.00	0.00
Retention %	100.00	89.58	97.09	89.61
T2 %affiliated ATS	5.79	5.92	6.70	6.34
Retention %	100.00	76.10	86.23	89.92
T3 %affiliated ATS	50.10	51.37	49.75	48.57
Retention %	100.00	83.20	88.18	100.00
T3-T1	50.10^{***}	51.37^{***}	49.75^{***}	48.56^{***}
T3-T2	44.31^{***}	45.46^{***}	43.05^{***}	42.22^{***}

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. *Order size (%ADV)* is the average order size as a percentage of average daily volume in the stock in September 2016. *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* 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. *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order. *Shortfall* 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 are measured as in effective spread. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Broker tercile	#Obs	Order size (%ADV)	Fill rate	Arrival spread (bp)	Eff. spread (bp)	Delay (bp)	Shortfall (bp)
A: All stocks							
T1 (least %affiliated ATS)	51,535	0.39%	45.68%	11.02	1.13	3.68	4.16
T2	50,949	0.64%	27.83%	22.63	3.30	5.89	6.64
T3 (most %affiliated ATS)	49,232	0.42%	16.92%	22.35	3.32	10.26	10.67
T1-T3		−0.03%	28.76%***	−11.33***	−2.19***	−6.59***	−6.51***
T2-T3		0.22%***	10.90%***	0.28	−0.02	−4.37***	−4.03***
B: Large stocks							
T1 (least %affiliated ATS)	25,833	0.12%	49.20%	3.89	0.49	1.90	2.19
T2	18,173	0.10%	35.94%	4.53	1.62	2.67	2.77
T3 (most %affiliated ATS)	16,545	0.06%	20.85%	3.50	2.12	4.77	4.84
T1-T3		0.06%***	28.34%***	0.39***	−1.63***	−2.87***	−2.65***
T2-T3		0.04%***	15.09%***	1.03***	−0.49***	−2.10***	−2.07***
C: Medium stocks							
T1 (least %affiliated ATS)	19,468	0.44%	42.85%	13.13	0.88	4.28	4.83
T2	20,885	0.46%	24.11%	19.61	2.66	4.78	5.09
T3 (most %affiliated ATS)	20,394	0.20%	15.26%	16.50	2.94	9.75	9.96
T1-T3		0.24%***	27.60%***	−3.36***	−2.06***	−5.46***	−5.13***
T2-T3		0.26%***	8.86%***	3.11***	−0.29	−4.97***	−4.87***
D: Small stocks							
T1 (least %affiliated ATS)	6,234	1.34%	39.93%	34.01	5.05	9.17	10.23
T2	11,891	1.79%	21.94%	55.60	7.93	12.78	15.26
T3 (most %affiliated ATS)	12,293	1.26%	14.39%	57.44	6.16	18.52	19.69
T1-T3		0.08%	25.54%***	−23.43***	−1.12	−9.35***	−9.46***
T2-T3		0.53%**	7.55%***	−1.84**	1.77**	−5.74***	−4.42***

Table 5: ATS affiliation and execution quality, regression analysis

This table presents results for 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*, 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; *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order; *Shortfall* 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. 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; *depth*, the stock-day time-weighted average dollar depth at the best bid and ask; *imbalance* the stock-day %trade volume imbalance; *RV*, the daily sum of squared stock-level 5-minute midquote log returns; *price*, the natural log of stock price; and *market cap*, the natural log of market capitalization in thousands. p-values, obtained from standard errors clustered by stock and day, are presented in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	Dependent variable:											
	Fill rate (%)			Effective spread (bp)			Delay (bp)			Shortfall (bp)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
%Affiliated ATS	-38.91^{***}	-37.49^{***}	-37.37^{***}	0.65	-0.25	-0.27	7.12^{***}	6.32^{***}	6.20^{***}	6.91^{***}	6.03^{***}	5.84^{***}
	$(<.001)$	$(<.001)$	$(<.001)$	$(.101)$	$(.528)$	$(.487)$	$(<.001)$	$(<.001)$	$(<.001)$	$(<.001)$	$(<.001)$	$(<.001)$
Order size		1.18^{***}	1.19^{***}		1.05^{***}	1.10^{***}		1.93^{***}	2.02^{***}		1.73^{***}	1.83^{***}
		$(<.001)$	$(<.001)$		$(<.001)$	$(<.001)$		$(<.001)$	$(<.001)$		$(<.001)$	$(<.001)$
Arrival spread (bp)		-0.10^{***}	-0.12^{***}		0.12^{***}	0.08^{***}		0.07^{***}	0.05		0.10^{***}	0.07^{**}
		$(<.001)$	$(<.001)$		$(<.001)$	$(.003)$		$(.009)$	$(.131)$		$(<.001)$	$(.046)$
Depth		1.37^{***}	3.45^{***}		0.26	0.72		-0.24	2.01^{**}		0.06	2.28^{**}
		$(.003)$	$(<.001)$		$(.244)$	$(.118)$		$(.504)$	$(.027)$		$(.876)$	$(.016)$
Imbalance		3.15^{**}	-0.20		4.62^{**}	-0.24		2.42	2.54		4.60^{*}	2.52
		$(.040)$	$(.810)$		$(.045)$	$(.898)$		$(.364)$	$(.298)$		$(.097)$	$(.341)$
RV (bp)		0.00^{***}	0.00^{***}		0.00^{*}	0.00^{**}		0.00^{***}	0.00^{**}		0.00^{***}	0.00^{**}
		$(.004)$	$(.007)$		$(.051)$	$(.038)$		$(.004)$	$(.025)$		$(.004)$	$(.024)$
Price		-1.50^{***}			0.30^{*}			0.26			0.25	
		$(<.001)$			$(.057)$			$(.445)$			$(.469)$	
Market cap		1.74^{***}			-0.33^{**}			-1.23^{***}			-1.32^{***}	
		$(<.001)$			$(.027)$			$(<.001)$			$(<.001)$	
Stock fixed effects	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Observations	151,716	151,716	151,716	133,810	133,810	133,810	151,716	151,716	151,716	151,716	151,716	151,716
Adjusted R^2	.11	.16	.17	.00	.01	.03	.00	.01	.02	.00	.01	.02

Table 6: ATS affiliation and execution quality: Not-held orders

This table presents results for regressions examining the relationship between ATS affiliation and execution quality for orders marked as held and not-held. Units of observation are broker-order type-stock-day top order quantity weighted averages. Dependent variables include *Fill rate*, the ratio of executed quantity to top order quantity; *Effective spread*, 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; *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order; *Shortfall* 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. Independent variables include *NH*, an indicator variable equal to one for not-held orders and zero otherwise; *T3*, an indicator variable that is equal to one for T3 brokers (brokers characterized by the most affiliated ats routing) 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 arrives at a broker; *depth*, the stock-day time-weighted average dollar depth at the best bid and ask; *imbalance*, the stock-day %trade volume imbalance; and *RV*, the daily sum of squared stock-level 5-minute midquote log returns. p-values, obtained from standard errors clustered by stock and day, are presented in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	Dependent variable:			
	Fill rate (%)	Effective spread (bp)	Delay (bp)	Shortfall (bp)
NH×T3	-2.87^{**}	4.71^{***}	2.18^{**}	3.19^{***}
	(.045)	(<.001)	(.025)	(.002)
NH	-1.82^{*}	0.46	1.14	0.39
	(.052)	(.101)	(.113)	(.564)
T3	-12.65^{***}	-3.93^{***}	1.55^{*}	0.42
	(<.001)	(<.001)	(.077)	(.604)
Order size	0.30	0.87^{***}	1.87^{***}	1.55^{***}
	(.242)	(<.001)	(<.001)	(<.001)
Arrival spread (BP)	-0.13^{***}	0.09^{***}	0.05^{*}	0.08^{**}
	(<.001)	(<.001)	(.089)	(.013)
Depth	3.58^{***}	0.65	1.69^{*}	2.00^{**}
	(<.001)	(.117)	(.054)	(.031)
Imbalance	-0.44	-0.26	1.76	1.80
	(.639)	(.882)	(.447)	(.502)
RV (bp)	0.00^{***}	0.00^{*}	0.00^{***}	0.00^{***}
	(.002)	(.088)	(.010)	(.009)
Stock fixed effects	Y	Y	Y	Y
Observations	185,093	164,015	185,093	185,093
Adjusted R^2	.10	.03	.02	.02

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. Each column corresponds to a regression specification. 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. *%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 (%ADV)* is the average order size as a percentage of stock average daily volume during September 2016. *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*, 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; *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order; and *Shortfall* measures the implementation shortfall using the closing price of the day as the fill price for the unexecuted portion of the order. Independent variables include *T3*, an indicator variable that is equal to one for a T3 broker and zero otherwise; *order size*, the natural log of the average order size; and *arrival spread*, the average percentage quoted NBBO spread at the time an order is placed with a broker. p-values, obtained from standard errors clustered by stock and day, are presented in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

A: Descriptive statistics

	#Observations		#Stocks		%ATS		%Affiliated ATS		%Unaffiliated ATS	
	Non-T3	T3	Non-T3	T3	Non-T3	T3	Non-T3	T3	Non-T3	T3
Full sample	102,484	49,232	300	300	17.63%	63.49%	3.19%	49.85%	14.44%	13.64%
Matched sample	21,104	21,104	300	300	49.87%	51.00%	7.14%	41.51%	42.73%	9.49%

	Order size (%ADV)		Volume (mm)		Price ($)		Market cap ($mm)	
	Non-T3	T3	Non-T3	T3	Non-T3	T3	Non-T3	T3
Full sample	0.51%	0.42%	3632.80	2522.55	65.93	57.78	43634.03	29545.99
Matched sample	1.02%	0.38%	3042.84	3042.84	58.02	58.02	34005.35	34005.35

B: Matched regression

	Dependent variable:			
	Fill rate (%)	Effective spread (bp)	Delay (bp)	Shortfall (bp)
T3	-5.36^{***}	-0.88^{*}	3.03^{***}	2.22^{***}
	(<.001)	(.085)	(<.001)	(<.001)
Order size	3.60^{***}	0.39^{**}	2.22^{***}	1.81^{***}
	(<.001)	(.032)	(<.001)	(<.001)
Arrival spread (bp)	-0.10^{***}	0.05^{*}	0.14^{***}	0.15^{***}
	(<.001)	(.099)	(<.001)	(<.001)
Match pair fixed effects	*Y*	*Y*	*Y*	*Y*
Observations	42,208	35,368	42,208	42,208
Adjusted R^2	.32	.08	.16	.17

Table 8: Determinants of venue choice

This table presents the cross-sectional determinants of venue choice. Units of observation are T3 or non-T3-stock-day averages of broker-stock-day proportions. Panel A presents the determinants of venue choice for non-T3 brokers, and panel B presents determinants for tercile 3 (*T3*, characterized by the most routing to affiliated ATSs) brokers. Dependent variables in panel A include *ATS ex qty*, the stock-day average proportion of executed quantity at ATSs; and *ATS rt qty*, the stock-day average proportion of routed quantity sent to ATSs. Dependent variables in panel B include *affiliated ATS ex qty*, the stock-day average proportion of executed quantity at affiliated ATSs; and *affiliated ATS rt qty*, the stock-day average proportion of routed quantity sent to affiliated ATSs. Independent variables include *market cap*, the natural log of market capitalization in thousands; *volume*, the natural log of stock trading volume; *price*, the natural log of stock price; *spread*, stock-day time-weighted average percentage quoted bid ask spread; *depth*, the stock-day time-weighted average dollar depth at the best bid and ask; *imbalance* the stock-day %trade volume imbalance; and *RV*, the daily sum of squared stock-level 5-minute midquote log returns. p-values, obtained from standard errors clustered by stock and day, are presented in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

A: Non-T3 brokers

	Dependent variable:													
	ATS ex qty (%)							ATS rt qty (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market cap	0.29***							−1.31***						
	(.005)							(<.001)						
Volume		0.72***							−1.78***					
		(<.001)							(<.001)					
Price			−0.46**							−2.42***				
			(.030)							(<.001)				
Spread (bps)				−0.00							0.06***			
				(.780)							(<.001)			
Depth					0.61***							−0.73**		
					(<.001)							(.027)		
Imbalance						−3.16							32.24***	
						(.156)							(<.001)	
RV							0.02**							−0.01
							(.027)							(.213)
Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,114	6,114	6,114	6,114	6,114	6,114	6,114	6,297	6,297	6,297	6,280	6,297	6,297	6,276
Adjusted R^2	.01	.05	.01	.01	.01	.01	.01	.06	.15	.05	.20	.02	.26	.04

B: T3 brokers

	Dependent variable:													
	Affiliated ATS ex qty (%)							Affiliated ATS rt qty (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market cap	0.66***							−0.53*						
	(<.001)							(.051)						
Volume		1.29***							−0.58**					
		(<.001)							(.042)					
Price			−0.23							−0.26				
			(.479)							(.596)				
Spread (bps)				−0.03***							0.00			
				(<.001)							(.898)			
Depth					1.57***							−0.44		
					(<.001)							(.271)		
Imbalance						−10.42***							3.34	
						(<.001)							(.358)	
RV							0.01							−0.02*
							(.107)							(.079)
Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,153	6,153	6,153	6,152	6,153	6,153	6,152	6,269	6,269	6,269	6,255	6,269	6,269	6,253
Adjusted R^2	.02	.07	.01	.03	.03	.03	.01	.01	.02	.01	.01	.01	.01	.01

Table 9: Horse races

This table presents results for horse races of ATS midpoint pegged and primary 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 orders that have the same stock, date, order side, arriving during the same NBBO price state. The first order in the order pair still must be active, unmodified, and not have obtained an execution when the second order in the order pair is routed. At least one of the matched orders must recieve a partial or complete, while the other order is still active and unmodified. 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 500 ms 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 500 ms prior to its paired order. *Tie* is the percentage of horseraces in which the affiliated route filled within 500 ms 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. Test statistics are obtained from standard errors clustered by stock and day. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

A: Descriptive statistics

Matched pair type	# of order pairs	Avg. affiliated fill rate	Avg. unaffiliated fill rate	Both fill
Midpoint peg	1464349	41.12%	49.98%***	11.42%
Primary peg	747642	34.75%	64.78%***	9.14%

B: Horse races

Matched pair type	Affiliated fills first	Unaffiliated fills first	Tie	Good fill ratio	
				Affiliated	Unaffiliated
Midpoint peg	42.01%	53.27%***	4.72%	61.75%	62.45%
Primary peg	32.17%	63.24%***	4.59%	50.61%	50.56%

Table 10: ATS affiliation and execution quality: Tick Size Pilot

This table presents results for difference-in-difference-in-differences regressions comparing the execution quality of tercile 3 (*T3* brokers, characterized by the most routing to affiliated ATSs) to matched non-T3 brokers surrounding the implementation of the trade-at rule of the U.S. tick size pilot program during September and November 2016. Units of observation are broker-stock-day top order quantity weighted averages. Panel A includes treatment group 3 (*G3*) stocks subject to a trade-at rule and control stocks, and panel B includes G3 and treatment group 2 (*G2*) stocks. T3 brokers affiliated with ATSs whose percentage of trading volume executed at the NBBO midpoint is less than or equal to the ATS-level pre-period median are matched with a T1 or T2 broker based on the broker-stock-day average proportion of share quantity routed to ATSs during September 2016 using nearest-neighbor one-to-one propensity score matching. Dependent variables include *ATS rt qty*, the percentage of routed quantity sent to ATSs; *Fill rate*, the ratio of executed quantity to top order quantity; *Effective spread*, 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; *Delay* measures price drift over the life cycle and cleanup costs using the closing price of the day as the fill price for the unexecuted portion of the order; *Shortfall* 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. Independent variables include *G3*, an indicator variable equal to one for G3 stocks and zero otherwise; *T3*, an indicator variable equal to one for T3 brokers and zero otherwise; *post*, an indicator variable equal to one for November 2016 and zero otherwise. Additional independent variables not reported include *order size*, the natural log of the average order size; *imbalance* the stock-day %trade volume imbalance; *RV*, the daily sum of squared stock-level 5-minute midquote log returns; *price*, the natural log of average stock price during September 2016; *market cap*, the natural log of average market capitalization in thousands during September 2016; and *VIX*, the daily VIX index. p-values, obtained from standard errors clustered by stock and day, are presented in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	Dependent variable:									
	A: G3 and control stocks					*B: G3 and G2 stocks*				
	ATS rt qty (%)	Fill rate (%)	Effective spread (bp)	Delay (bp)	Shortfall (bp)	ATS rt qty (%)	Fill rate (%)	Effective spread (bp)	Delay (bp)	Shortfall (bp)
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Post × G3 × T3	−2.77***	2.53***	−6.75***	−9.27***	−8.90***	−5.77***	2.04**	−3.93**	−4.30**	−4.07**
	(.003)	(.001)	(<.001)	(<.001)	(<.001)	(<.001)	(.018)	(.013)	(.031)	(.042)
G3	0.48	0.08	−0.47	−0.59	−0.61	0.29	0.42	0.78	−0.04	−0.00
	(.482)	(.897)	(.486)	(.438)	(.441)	(.729)	(.626)	(.386)	(.973)	(.997)
T3	8.11***	−21.51***	3.05***	6.48***	6.17***	6.13***	−20.19***	4.34***	6.75***	6.72***
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Post	−2.35**	0.42	1.14*	2.02	1.67	−2.47***	0.41	3.22***	1.02	0.47
	(.013)	(.715)	(.085)	(.129)	(.202)	(.007)	(.712)	(.001)	(.581)	(.806)
G3 × T3	−1.15	0.29	0.27	0.78	0.74	−0.84	0.16	−0.56	0.22	0.12
	(.312)	(.701)	(.741)	(.408)	(.439)	(.544)	(.869)	(.593)	(.842)	(.922)
Post × G3	−4.43***	2.19***	5.18***	8.84***	8.36***	−4.80***	2.53***	3.28**	9.77***	9.57***
	(<.001)	(.002)	(<.001)	(<.001)	(<.001)	(<.001)	(.003)	(.013)	(<.001)	(<.001)
Post × T3	−0.25	2.50**	−0.86	1.57	1.88	3.64***	2.38**	−3.89***	−3.23**	−2.90*
	(.823)	(.035)	(.402)	(.193)	(.115)	(.002)	(.050)	(.001)	(.041)	(.072)
Observations	317,191	317,191	275,312	317,191	317,191	149,796	149,796	129,032	149,796	149,796
Adjusted R^2	.02	.10	.00	.01	.01	.02	.09	.00	.01	.01