The Value of Intermediation in the Stock Market

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Abstract

Brokers continue to play a critical role in intermediating stock market transactions for institutional investors. More than half of all institutional investor order flow is still executed by high-touch (non-electronic) brokers. Despite the importance of brokers, we have limited information on what drives investors' choices among brokers. We develop an empirical model of intermediary choice to investigate how institutional investors trade across different brokers. We analyze investors' responsiveness to the commissions paid, the broker's ability to efficiently execute the trades, as well as access to better research analysts and order flow information. We find that investors are relatively insensitive to commissions, but on average value research, execution, and access to information. Furthermore, using trader-level data we find that investors are more likely to trade with brokers who are physically located closer and are less likely to trade with brokers whose traders have misbehaved in the past. There is also significant heterogeneity across investors, with the best performing investors placing a higher value on order flow information and less value on research. We use the model to analyze several counterfactuals highlighting key inefficiencies in the market that raise trading costs.

Keywords: Financial Intermediation, Institutional Investors, Broker Networks, Equity Trading.

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I Introduction

The last decade has seen a proliferation of trading platforms that have made the modern equity markets highly fragmented. In the United States alone, there are different venues from a dozen of national securities exchanges to roughly forty alternative trading systems and other off-exchange systems (Maglaras et al. 2012 and OECD, 2016). The structure of financial markets, and in particular the way in which investors interact with each other and the market, is crucial in determining market efficiency and how information gets ultimately incorporated into prices. To complicate matters, most investors do not access equity markets directly. Instead, they delegate the decision of which venue to trade in to their broker. In principle, the broker's and client's interests are aligned, as the broker earns a profit from the commission only if the client's order executes. However, brokers might potentially execute the order to maximize their own profitability, rather than serving their clients' interest. These issues have attracted the attention of the regulators and policymakers. Recent policy interventions, such as MiFID II, aim to hold investment managers accountable to best execution standards, and to offer greater transparency around the services offered by brokers to investors.

Yet, we know very little about how institutional investors route their orders across different intermediaries. Specifically, the central question is what are the key dimensions that investors trade off in making these decisions. In fact, market fragmentation has further increased the intermediaries' incentives to attract customers' orders by advertising different services, from execution to access to better research. A key challenge in studying these issues is posed by investors' concerns about the confidentiality of their trades.

We overcome this challenge in two ways. First, we develop an empirical model of brokerage firm choice to investigate the execution decisions of institutional investors. We examine an investor's decision on *where* to execute their trade, conditional on the investor's initial decision to trade a specific security. We abstract away from the trade idea generation process, and instead focus on the investor's decision on which broker to trade with in order to minimize trading costs. In the model investors exogenously generate trades and must decide which broker to route their trade through. We model the investor's execution decision as a discrete choice problem. Investors choose the broker that maximizes their expected profits, or put differently, the broker that minimizes their expected execution costs. When deciding among brokers, investors trade off transaction commissions, quality of execution (i.e. price impact), and the quality of other services provided by the broker such as research and order flow information.

Second, we estimate our broker choice model using a rich micro-data set covering hundreds of millions of equity transactions. Our base data set comes from Abel Noser Solutions, formerly Ancerno Ltd. The company performs transaction cost analysis for institutional investors and makes the data available for academic research under the agreement of non-disclosure of institutional identity. Our data set covers the period 1999 to 2014. The data set includes trade-level data for institutional investors, covering a up to 20% of the institutional trading volume in the U.S. stock market (Puckett and Yan (2011), Hu, Jo, Wang, and Xie (2018)). At the trade-level, we observe:

the transaction date and time, the execution price; the number of shares that are traded, the side (buy or sell) and the stock CUSIP. We also observe the identity of the investment manager placing the trade and the broker executing the corresponding trade.

We merge the Ancerno data set with rich brokerage firm level data from several sources. First, we merge the Ancerno data set with sell-side equity analyst data from Thomson Reuters I/B/E/S and Institutional Investor. We use the I/B/E/S data to measure each brokerage firm's equity research coverage across various equity sectors over time. We measure the quality of research using data from Institutional Investor; every year Institutional Investor publishes the "All-American Equity Research Team," which lists the top three equity analysts in each sector. Lastly, we supplement the Ancerno data with equity trader level data from BrokerCheck. BrokerCheck is a website operated by the Financial Industry Regulatory Authority (FINRA), and the website contains rich information on the universe of individuals registered in the securities industry (See Egan, Matvos, and Seru 2016 for further details). The BrokerCheck data contains individual level information on the equity traders employed by the brokerage firms in our data set. For each trader we observe his/her complete employment history, qualifications, and whether or not the trader has any disclosure on his/her record such as a customer dispute or regulatory offense. In sum, our data set contains transaction level data accounting for a substantial fraction of institutional equity trading volume in the U.S. where we also have detailed individual level information on the parties involved in the transactions.

We estimate our discrete choice/demand framework following the workhorse models used in the industrial organization literature (Berry (1994), Berry, Levinsohn, and Pakes (1995)). Our setting and data is ideal for demand estimation for several reasons. First, we observe individual investors making tens of thousands of execution decisions in our data. This rich data allows us to estimate our discrete choice model at the investor level, allowing us to flexibly estimate each individual investor's execution preferences without imposing any parametric distributional assumptions. Second, a common problem in the demand estimation literature is the endogeneity of prices, or in this case commissions. If brokerage firms are able to flexibly adjust commissions based on the actions and preferences of investors, commissions will be endogenous. We are able to address the endogeneity of commissions through an instrumental variables approach that exploits unique institutional features of the brokerage industry. Specifically, brokerage firms charge commissions in terms of cents per share, typically rounded to the nearest whole number. This rigidity in the way commissions are set provides exogenous variation in the effective commissions paid by investors.

We use our framework to better understand how institutional investors trade-off commissions, quality of execution, research, and order flow information when deciding where to execute trades. The first result is that the majority of institutional investors are relatively price insensitive. The average demand elasticity in our data set is roughly 0.3-0.4. The estimates imply that if a broker increases the commission it charges by 1%, its trading volumes will go down by an associated -0.40%. This suggests that commissions are not a key consideration for investors and a key competitive lever for brokers. However, having the ability to estimate the impact of these commissions on the investors' decisions allows us to precisely quantify all the other important dimensions driving their choices.

A key factor driving an investor's trade decision is the quality of execution. Traders may differ in there ability to execute large trader orders without moving the market price of a stock. We measure the quality of execution at the trade level as the execution price relative to some benchmark price. We explore three different benchmarks: the opening price on the day of the order, the price at the placement of the investor's first order to any broker, and the price of at the placement of the investor's order. Given the investors objective to predict future price impact and the inevitable measurement error in our measures, we instrument for the investor's expectations of a broker's price impact with the broker's past price impact history. We find that a one standard deviation improvement in execution is worth 12bps.

Brokers also offer research to their clients through equity analysts covering different sectors, and tailored presentations about potential changes in fundamentals. We can test whether investors value research when executing trades. One can imagine investors valuing the access to better analysts that themselves enjoy more privileged and direct access to the firm's management; and they might value the sales pitches around trade ideas that brokers tend to routinely do to attract orders. Our results show that the average investor is willing to pay an additional 2bps per trade in order to have access to a top equity research analyst.

We can enrich our analysis by investigating whether brokers are considered a valuable source of order flow information. We measure that in two ways. First, following Barbon, Di Maggio, Franzoni, and Landier (2018) we define a broker informed if he has traded with an informed investor. We find that investors are willing to pay between 5bps and 15bps more to trade with a broker who has received privileged information about informed order flow. Second, following Di Maggio, Franzoni, Kermani, and Sommavilla (2018) we can capture the broker's access to information with its centrality in the network of relationships between managers and brokers. We find that investors are willing to an additional 1.5bps to trade with a more central broker.

We also observe that investor's value characteristics of the individual traders employed by the brokerage firms. Investors are less likely to trade with a brokerage firm whose equity traders are involved in more client disputes and regulatory offenses. We also find evidence that investors prefer to trade with equity traders located in the same city. Even though equity transactions are placed either electronically or over the phone, physical proximity to the broker and traders influences an investor's trading decision.

Lastly, we use our rich setting to explore how the execution decisions and preferences vary across investors. For example, while we find that the average investor values sell-side equity research, we find that roughly 33% of investors place literally no value on sell-side research. This has potentially important implications for the bundling of services provided by brokers. Currently, brokers typically bundle their services, where the broker bundles execution, research, and other brokerage services into one package. Our analysis suggests that this type of bundling may lead to an inefficient over-production of sell-side research as many investors are effectively forced to purchase research that they do not value. Hedge funds are among those investors who place a lower value on sell-side research. Conversely, hedge fund investors appear to place a premium on the other type of information produced brokerage firms, such as whether or not the broker has received privileged information about informed order flow.

Overall, we build and estimate a model of investor execution that allows us to evaluate investor's trading decisions and evaluate several policies to improve the current financial structure. Specifically we find that lower trading costs could be achieved by restructuring the network. We can also explicitly bound the cost of allowing the average investor to trade with one more counterparty between 2-3bps.

I.A Related Literature

The paper relates to different strands of the literature. From a theoretical perspective, our work draws inspiration from recent papers that highlight a role of financial intermediaries in operating as information catalysts. In particular, Babus and Kondor (2018) model the trading behavior of privately-informed dealers in OTC markets. In their theory, central intermediaries acquire more information than peripheral ones. We differ from this paper in that we focus on a centralized market, the stock market. The brokers that we study only convey their client's trades to the market, they do not take positions using their inventory. However, we build on these author's intuition that central intermediaries are able to achieve an informational advantage. Hence, the clients of these intermediaries also benefit from an information edge. Glode and Opp (2016) explain that a rationale for intermediaries in financial markets is their ability to reduce information asymmetry and improve trading efficiency. In the same vein, one of the functions of brokers in our empirical setup is to intermediate information. Moreover, brokers in our setup can reduce the trading costs of their clients. In this sense, our analysis incorporates the notion that intermediaries emerge to reduce transaction costs (Townsend (1978)). More generally, our analysis is also inspired by work studying information percolation in financial markets, such as Duffie and Manso (2007) and Duffie, Malamud, and Manso (2015).

In the empirical literature, some work points out an important role of brokers in information transmission. Using an earlier version of our data, Goldstein, Irvine, Kandel, and Wiener (2009)provide a useful description of the institutional brokerage industry. They show that institutions value long-term relations with brokers. They find a bi-modal distribution of fees corresponding to premium and discount brokerage services, where premium services include access to research. Moreover, they document that the best institutional clients are compensated with the allocation of superior information around changes of analyst recommendations. Other work shows that the best institutional clients of brokers also receive privileged information about informed order flow (Di Maggio, Franzoni, Kermani, and Sommavilla (2018)) and ongoing fire sales (Barbon, Di Maggio, Franzoni, and Landier (2018)). Evidence that brokers pass valuable information to selected clients is also present in Irvine, Lipson, and Puckett (2006) regarding future analyst recommendations, in McNally, Shkilko, and Smith (2015) and Li, Mukherjee, and Sen (2017) regarding insiders' order flow, and in Chung and Kang (2016) for hedge fund trading strategies. Our incremental contribution is to incorporate the implications of some of this work within a structural model to compute the value of broker intermediation for institutional clients.

Methodologically, we estimate demand for brokerage services using variation in broker's market share and a standard model of demand (Berry (1994), Berry, Levinsohn, and Pakes (1995)). This methodology allows us to study interesting counterfactuals. Using a similar approach, Egan, Hortaçsu, and Matvos (2017) estimate demand for bank deposits.

II Framework

We develop an empirical model of broker choice. Specifically, we examine an investor's decision on *where* to execute their trade, conditional on the investor's initial decision to trade a specific security. We abstract away from the trade idea generation process and instead focus on the investor's decision of which broker to trade with in order to minimize trading costs.

We model an investor's execution decision as a multinomial choice problem where the investor has a trade order she needs to execute, and can route her order through through any of the n available brokers denoted $l = 1, ...n$. Investors choose a broker based on the associated costs and services. For convenience and consistent with the literature on demand estimation, we initially write the investor's problem in terms of a utility maximization problem, but show below that the investor's utility maximization problem translates directly into the investor's profit maximization/cost minimization problem. The indirect utility derived by investor i of executing trade idea j in industry sector k through brokerage firm l at time t is given by

$$u_{ijklt} = -\alpha_i c_{iklt} + X'_{klt}\beta_i + \xi_{klt} + \epsilon_{ijklt} \quad (1)$$

Investors pay an investor-broker-sector specific commission c_{iklt} for executing a trade with broker l, from which she derives dis-utility $-\alpha_i c_{iklt}$. The parameter $\alpha_i > 0$ measures the investor's sensitivity to brokerage commissions. Note that the parameter α_i varies across investors which implies that investors have potentially different elasticities of demand.

Investors also derive utility from other brokerage services captured in the term $X'_{klt}\beta_i + \xi_{klt} + \epsilon_{ijklt}$. The vector X_{klt} is a vector of broker specific characteristics that reflect differences in execution services such as price impact, speed, and/or information. For example, some brokers may have more skilled traders than other firms and consequently provide better trade execution. Furthermore, trading ability may vary within a brokerage firm across different securities and over time. For example, Goldman Sach's could provide better execution for stocks in the technology sector while Morgan Stanley provides better execution for stocks in the financial sector. The vector X_{jkt} also captures the quality of research and other information services provided by the brokerage firms. For example, Goldman Sach's may offer better research coverage or be privy to better information regarding stocks in the technology sector than Goldman Sach's competitors. The vector β_i reflects investor i's preferences over the broker characteristics X_{klt}. We again allow preferences for the various brokerage services captured in X_{klt} to vary across investors. Some investors may place a higher value on sell-side research while others place a higher value on execution. The term ξ_{klt} is a time varying broker by sector unobservable demand/profit shock. For example, Goldman's Sach's ability to efficiently trade a stock may vary over time that is not captured in the vector X_{klt}. Last the variable ϵ_{ijklt} reflects a investor-trade-broker-security-time demand/profit shock that is i.i.d. across investors, brokers and time. The term ϵ_{ijklt} captures preference heterogeneity within an investor across different trade ideas. For example, an investor may prefer to route a particular trade in the financial sector to Goldman Sachs while routing other trades in the financial sector to Morgan Stanley. The parameter ϵ_{ijklt} introduces additional heterogeneity to help explain why we see a given investor trade with multiple brokers at the same time in a given sector.

Assuming that investors only derive utility from expected profits, the above indirect utility formulation maps directly into the expected profits of the investor. We can write the investor's expected profits of executing trade j in sector k with broker l at time t as

$$E[\pi_{ijklt}] = -c_{ilkt} + \frac{1}{\alpha_i}X'_{klt}\beta_i + \frac{1}{\alpha_i}\xi_{klt} + \frac{1}{\alpha_i}\epsilon_{ijklt} \tag{2}$$

The term β_i/α_i captures how the various services offered by a brokerage firm, translate into an investor's profits.

Investors choose the brokerage firm in the set $\mathcal{L} = \{1, 2, ...n\}$ that maximizes the investor's expected profits

$$\max_{l\in\mathcal{L}} E[\pi_{ijklt}]$$

Under the assumption that the investor-broker-security-time specific profit shock, ϵ_{ijklt} profit shock is distributed i.i.d. Type 1 Extreme Value, as is standard in the multinomial choice literature, the probability that investor i executes her trade with firm l is given by

$$\Pr(l) = \frac{\exp\left(-\alpha_i c_{iklt} + X'_{klt}\beta_i + \xi_{klt}\right)}{\sum_{m\in\mathcal{L}}\exp\left(-\alpha_i c_{ikmt} + X'_{kmt}\beta_i + \xi_{kmt}\right)} \tag{3}$$

The above likelihood corresponds to the multinomial logit distribution and is the core of our estimation strategy below. The advantage of our framework is that it is straightforward to estimate in the data and allows us to precisely measure the trade-offs investors face when selecting a broker.

III Data

III.A Ancerno Data

We use information about institutional transactions from a Abel Noser Solutions, formerly Ancerno Ltd. (the name 'Ancerno' is commonly retained for this data set). The company performs transaction cost analysis for institutional investors and makes the data available for academic research under the agreement of non-disclosure of institutional identity. We have access to data covering the period from 1999 to 2014. Previous literature has established the merits of this data set (see Hu, Jo, Wang, and Xie (2018) for a detailed description of the structure and coverage of the data).

First, clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggesting that the data should not suffer from self-reporting bias. Furthermore, Ancerno collects trade-level information directly from hedge funds and mutual funds when these use Ancerno for transaction cost analysis. However, another source of information derives from pension funds instructing the managers they have invested in to release their trading activities to Ancerno as part of their requirements under ERISA regulation. Third, Ancerno is free of survivorship biases as it includes information about institutions that were reporting in the past but at some point terminated their relationship with Ancerno. Previous studies, such as Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2012, 2013), have shown that the characteristics of stocks traded and held by Ancerno institutions and the return performance of the trades are comparable to those in 13F mandatory filings. Some estimates suggest that Ancerno covers between 10% and 19% of the institutional trading volume in the U.S. stock market (Puckett and Yan (2011), Hu, Jo, Wang, and Xie (2018)). Ancerno information is organized on different layers. At the trade-level, we know: the transaction date and time at the minute precision (only for a subset of trades), the execution price; the number of shares that are traded, the side (buy or sell) and the stock CUSIP. Our analysis is carried out at the ticket level, i.e. we aggregate all trades on the same stock, on the same side of market (buy or sell), by the same manager, executed through the same broker, on the same day.

III.B Equity Research Data

To help examine the different factors driving an investors execution choice, we match our trade level Ancero data to sell-side equity research data from Thomson Reuters I/B/E/S and Institutional Investor. Thomson Reuters I/B/E/S is a database that provides equity analyst recommendations. We use the I/B/E/S data to determine each brokerage firms analyst coverage for each sector over time. We merge our trade level data with the I/B/E/S equity analyst recommendations at the brokerage firm, by year, by industry (GICS 6 Industry Code) level. Table 1 displays the corresponding summary statistics. The key variable of interest is the number of analysts employed by a brokerage firm in a given sector. The average brokerage firm employs 1.49 analysts in a given sector.

We also merge our trade level data with analyst data from Institutional Investor. Each year, Institutional Investor publishes an "All-America Research Team" where it ranks the top three equity analysts in a given sector for that year. We use the Institutional Investor data to determine the number of top rated analysts employed by each brokerage firm in each sector and year. We merge our trade level data with the All-American Research Team data at the year by sector by brokerage firm level. Table 1 displays the corresponding summary statistics. The average firm in our sample employs 0.16 top analysts in a given sector and year.

III.C BrokerCheck Data

We also examine how execution varies with quality of a firm's traders. We merge our trade level data with equity trader data from BrokerCheck. The Financial Industry Regulatory Authority (FINRA) maintains the website BrokerCheck which contains employment, qualification, and disclosure history for the universe of registered securities representatives over the past ten years. Our data covers the universe of registered securities representatives over the period 2005-2017 as described further in Egan, Matvos and Seru (2016). Equity traders must be registered with FINRA as securities representatives. The BrokerCheck database contains details on many securities representatives in addition to equity traders such as financial advisers, futures traders, etc. We determine which individuals in BrokerCheck are equity traders based on whether or not the individual has a Series 55 license. The Series 55 license, known as the Equity Trader Qualification License, entitles an individual to participate in equity trading. There were roughly 18,000 actively registered individuals licensed to trade equities in the U.S. in 2017. For each trader, we observe the trader's complete employment history. The average trader in our sample has 14 years experience in the industry. FINRA requires that registered representatives report any customer disputes, regulatory offenses, and/or criminal offenses. We examine whether the traders in our sample engage in misconduct, where misconduct is defined as per Egan, Matvos and Seru (2016) as any customer disputes that resulted in a settlement/award, regulatory offenses, criminal offenses, and/or terminations for cause. Roughly 6.50% of the equity traders in our sample have a past record of misconduct. We merge the BrokerCheck data with our trade level data at the broker by year level. Although we observe the identities of each trader, we do not observe the sector they trade in. Table 1 indicates that at the average brokerage firm in our sample, roughly 0.21% of the traders received a misconduct related disclosure in a given year.

Using the BrokerCheck data we are also able to determine the physical office locations of the brokerage firm traders and many of the investors of our data set. We calculate the physical distance in miles between between each broker-investor pair, based on the modal zip code of a broker's equity traders and the modal zip code of the investor's employees that are registered with FINRA. The average distance between an investor and a broker in our sample is 650 miles, though 33% of our broker-investor trading pairs are within 100 miles of each other.

IV Estimation

We use our Ancerno micro transaction level data to estimate our broker choice/ demand model from II. The model is straightforward to take to the data and allows us to determine how investors value the services brokerage firms provide. Our estimation procedure follows most closely follows Berry (1994) and Berry Leveninsohn Pakes (1995). However, the extensive and detailed nature of our data allows for a rich flexible estimation procedure where we are able to estimate the Berry (1994) model at the investor level. We observe tens of thousands of choices for each individual investor which allows us to flexibly recover the individual preferences of each investor without imposing any distributional assumptions over investor preferences.

To facilitate estimation we aggregate the individual trades an investor makes at the month by sector by broker level. In other words we define the market at the investor by month by sector level. We make two further adjustments to the the Ancerno data set. In our baseline estimation we focus on investor buy trades rather than sell trades. Sell trades may involve short selling which is unobserved in our data set and may include additional costs. In our baseline analysis we also exclude the 350,000 informed order flow trades as identified in Barbon, Di Maggio, Franzoni, and Landier (2018). Excluding these trades from our baseline analysis allows us to investigate how the execution of informed order flow influences the execution decisions of other investors. In other words, how does informed order flow spill over to other investors.

IV.A Empirical Framework

Following our framework from Section II the share of trades investor i executes with broker l in market k at time t is can be written as

$$s_{iklt} = \frac{\exp\left(-\alpha_i c_{iklt} + X'_{klt}\beta_i + \xi_{klt}\right)}{\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i c_{ikmt} + X'_{kmt}\beta_i + \xi_{kmt}\right)} \tag{4}$$

Following Berry (1994) we can rewrite the share of broker l in a given market (month by investor by sector) as

$$\ln s_{iklt} = -\alpha_i c_{iklt} + X'_{klt}\beta_i + \xi_{klt} - \ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i c_{ikmt} + X'_{kmt}\beta_i + \xi_{kmt}\right)\right) \tag{5}$$

Notice that the term $\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i c_{ikmt} + X'_{kmt}\beta_i + \xi_{kmt}\right)\right)$ is constant in a given market Therefore we can estimate eq. (5) using linear regression where we include a market fixed effect (μ_{ikt}) to absorb the non-linear term $\ln\left(\sum_{l\in\mathcal{L}} \exp\left(-\alpha c_{ijlt} + X'_{jlt}\beta + \xi_{ljt}\right)\right)$.

$$\ln s_{iklt} = -\alpha_i c_{iklt} + X'_{klt}\beta_i + \mu_{lt} + \mu_{ikt} + \varepsilon_{iklt} \tag{6}$$

Where X_{klt} is our vector of broker by sector by time characteristics and μ_{lt} is a broker by time fixed effect. We describe the construction and details of each our broker characteristics X_{klt} in the proceeding section. One of the key advantages in our setting with our rich micro data is that we are able to estimate a flexible heterogeneous coefficients model using ordinary least squares.

Although we micro-found eq. (5) in a structural model, we are essentially regressing log trade volumes on a vector of broker characteristics. Micro-founding the demand system provides additional interpretation and allows us to investigate several counterfactuals in Section VII. However, our estimates have a reduced form interpretation as well, measuring the relationship between broker characteristics and trade volume.

In the proceeding section we describe each of the control variables used in our analysis. We then discuss some of empirical implementation issues associated with estimating eq (5) due to endogeneity and measurement error issues.

IV.B Broker Characteristics

We are interested in the factors that drive professional investors execution decisions across brokers. Using our rich data set described in Section III we analyze how commissions, research, quality of execution, and information drive investor decisions. Here, we provide a description of each variable, its measurement, and how we incorporate the variable in our estimation strategy. We measure each variable on a trade-by-trade basis, and then aggregate each variable at the broker-investor-sector-month level for our estimation as described above.

Commissions: Brokers typically charge investors a commission for each share of stock traded. We measure the commissions paid on a per trade basis as the total commission paid relative to the value of the transaction.

$$c_{ijklt} = \frac{Total\, Commission\, in\, USD_{ijklt}}{Value\, of\, Transaction\, in\, USD_{ijklt}}$$

The average commission on a transaction is 11 points (bp). Figure 1a displays the distribution of commissions paid by investors. There is substantial variation in commissions paid by investors. The standard deviation of commissions is 6bps and commissions range from zero to upwards of 20bps. To put these numbers in perspective, the average mutual fund over the period 2000-2014 charged an expense ratio of 0.87 and turned over 54% of its portfolio on average, per year (2018 Investment Company Factbook).

A standard problem in this type of choice/demand problem is the endogeneity of prices/commissions. If brokerage firms observe the error term ε_{iklt} prior to setting their commissions, commissions will be correlated with the unobservable term ε_{iklt}. For example, suppose a brokerage firm experiences a demand shock because it has particularly good information or is able to provide ample liquidity in a given month. This demand shock will show up in the unobservable ε_{iklt}. In response to the demand shock, the brokerage firm may find it optimal to increase the commissions it charges. The endogeneity problem will cause the coefficient $-\alpha$ to be biased upwards such that the OLS estimates will indicate investors are less price sensitive than they actually are.

We address the endogeneity problem using instrumental variables. A unique feature of the institutional setting is that most brokerage firms charge investors a fixed dollar amount per shares of stock traded, typically 2-6 cents per share. Figure 1b displays the distribution of commissions charged on a per share basis. As illustrated in the figure, the commissions are bunched around the whole numbers in terms of cents per share. However, the relevant metric for the investor is measuring commissions in percentage terms relative to the value of a transaction. We argue that a one cent increase in the commission per share is more costly when an investor is trading a stock that trades at $1 per share relative to a stock that trades at $1,000 per share. Consequently, the relevant way for an investor to evaluate commissions is in percentage terms.

We exploit the institutional commission setting feature of the brokerage industry to construct an instrument for commissions. We construct our instrument at the trade level as the inverse of the corresponding equity share price scaled by the average commission charged by brokerage firm l:

$$IV_{ijklt} = \frac{1}{Share\,Price_{jt}} \times Commission\,Per\bar{\ }Share\,In\,USD_l$$

The instrument is correlated with our measure of commissions in percentage terms c_{ijklt} because, all else equal, a decrease in the share price makes the fixed per-share commission more expensive on a relative basis. The instrument satisfies the exogeneity condition essentially as long as share price movements of a stock are orthogonal to the investor-broker-market-time specific demand shocks ε_{iklt}. While movement in stock prices would certainly be correlated with an investors decision to trade, what matters for our setting is that movements in stock prices are not correlated *who* an investor trades with. Recall that our regression specifications include broker-time and investor-sector-time fixed effects, thus the exogeneity condition requires that the share prices are uncorrelated with time varying quality differences across brokers.

Price Impact: Another key factor driving an investor's trade decision is the quality of execution. Traders may differ in there ability to execute large trader orders without moving the market price of a stock. We measure the quality of execution at the trade level as the execution price relative to some benchmark price

$$Price\,Impact_{ijklt} = \left| \frac{Execution\,Price_{ijklt} - Benchmark\,Price_{ijklt}}{Benchmark\,Price_{ijklt}} \right|$$

The benchmark price reflects the price of the stock prior to the order. We measure the benchmark using three different measures: the opening price on the day of the order, the price at the placement of the manager's first order to any broker, and the price of at the placement of the manager's order. In our regression analysis we then aggregate our three price impact measures at the broker-investor-sector-month level using weighted averages.

There are two potential concerns with our price impact measures. First, they are inevitably measured with noise. It is unlikely that investors are able to perfectly predict the price impact of their trades. This type of measurement error will potentially cause our estimates to be suffer from an attenuation bias. Second, we are using contemporaneous price impact as a control variable which includes information unavailable to investors at time t. Ideally, we would like to be able to control for an investor's expectations about the price impact at time t, given the investors information set at time $t-1$, $E[Price\,Impact_{ijklt}|\mathcal{I}_{t-1}]$.To address both issues we use both contemporaneous and lagged price impact as a proxies for an investors' expectations about the price impact:

$$E[Price\,Impact_{ijklt}|\mathcal{I}_{t-1}] = Price\,Impact_{ijklt} + \eta_{ijklt}$$

$$E[Price\,Impact_{ijklt}|\mathcal{I}_{t-1}] = Price\,Impact_{ijklt-1} + \nu_{ijklt}$$

We then use contemporaneous price impact as a proxy for investor expectations about price impact and use lagged price impact as an instrument. Provided that the measurement error η_{ijklt} is orthogonal to ν_{ijklt}, then using instrumental variables will help address the potential measurement error issues with our proxies for price impact.

Research: We measure the level and quality of a brokerage firms research coverage in a particular sector along three dimensions using our I/B/E/S and Institutional Investor data sets. First, we include the number of analysts a brokerage firm employs in a given sector and year. Second, we control for the number of top analysts as reported by Institutional Investor that the brokerage firm employs in a given sector and year. Last, we also control for the number of buy recommendations a brokerage firm has in a given sector and time. The recommendations of the analysts help us understand if investors prefer to trade with brokers with similar market views or with diverging market views. The recommendations also provide further indication as to how much investors rely on broker produced (sell-side) research. We focus only on buy recommendations because our trade execution analysis focuses on buy trades.

Information: Brokers may have access to different information in the market due to the structure of the market and the counterparties the brokers deal with on a daily basis. We use two different measures to capture the how informed a broker is. First, we measure calculate the eigenvector centrality of the broker in the network where we define the network at the sector by month level. The eigenvector centrality measure takes into account all direct and indirect trading partners (i.e. fund managers and other brokers) and is computed by assigning scores to all brokers in the network. What counts is not only the number of connections of a broker, but *who* the broker is connected to. One potential concern with the eigenvector centrality measure is that it is potentially endogenous. A better broker is likely to have more trading partners in the network. To address this issue, we residualize our broker-month-sector eigenvector centrality measure based on the number of trading partners the broker has in the corresponding month and sector. Thus our residualized eigenvector centrality measure effectively measures how central a broker is in the network, conditional its number of trading partner. Thus, variation in the centrality of a broker's trading partners drives our residualized measure of eigenvector centrality.

We also control for whether or not a broker is "informed" in a given market as per Barbon, Di Maggio, Franzoni, and Landier (2018). Barbon, Di Maggio, Franzoni, and Landier (2018) study the role brokers play in spreading order flow information. The authors find evidence suggesting that after executing an "informed" trade, brokers tend to share that information with other investors. Following the literature we define an "informed trade" as abnormally large (75th percentile) profitable trade made by a hedge fund. We identify roughly 350,000 informed trades in our sample of over 300 million trades. In our analysis we control for whether or not the broker received an informed trade in a given month and sector. To avoid obvious endogeneity issues, we estimate our main regression specification eq. (6) where we exclude these informed trades when computing the shares of each broker at the investor-sector-month-level.

Traders: Through FINRA's BrokerCheck database we observe detailed information on the equity traders employed by each brokerage firm. For each broker, we observe the number of traders the broker employs, the experience of those traders, and the percentage of traders receiving misconduct related disclosures in a given year (i.e. customer disputes resulting in a settlement, regulatory offenses, etc). We examine how these trader characteristics influence an investor's trading decision.

V Results

V.A Price Sensitivity

The first question we tried to address with out model is how sensitive institutional investors are with respect to fees. Table 2 displays the estimation results corresponding to our discrete model where we measure commissions in percentage terms relative to the value of the transaction. As mentioned earlier, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Column (1) controls for sector by investor by month fixed effect to capture any time varying shock that might affect the investor's willingness to trade in a particular sector in a specific month. Column (2) also control for broker fixed effects, while Column (3) present the most conservative specification where we also control for broker by time fixed effects.

Consistently across specifications, we find that the average demand elasticity in our data set is roughly 0.3-0.4. The estimates imply that if a broker increases the commission it charges by 1%, its trading volumes will go down by an associated -0.40%. This suggests that commissions are less of a key consideration for investors than one would have expected and are not a key competitive lever for brokers. However, having the ability to estimate the impact of these commissions on the investors' decisions allows us to precisely quantify all the other important dimensions driving their choices.

V.B Price Impact

Given the time and resources devoted by investors in making sure that it is optimized, quality of execution is likely to be a key consideration for investors. Since brokers will have access to different networks of clients and different infrastructures to match opposite-sign orders from their clients, execution might be quite heterogeneous across them. Furthermore, some brokers might be more specialized than others and so more adept to better execute orders in some stocks but not others.

We investigate how investors take execution into account when deciding where to route their orders in Table 3. Columns (1) and (2) presents the estimation when using the price at the time of the order as benchmark, while Columns (3) and (4) check whether the results differ when using the opening price as benchmark, and finally Columns (5) and (6) provides the results for the price of the investor's first order as benchmark. All specifications include sector by investor by month and broker by month fixed effects. Even columns show the results where we instrument for commissions, while odd columns presents the results when we also instrument price impact to alleviate concerns about measurement error.

Overall, the results are both statistically and economically significant. Specifically, we find that a one standard deviation improvement in execution is worth about 12bps. In other words, investors would be willing to pay more than three times the current fees in order to ensure a better execution.

V.C Value of Research

Most "high-touch" brokers try to attract clients' order flow by providing other type of services other than execution. One of the most visible services offered by brokers is access to research analysts covering an important cross section of sectors. In addition to provide recommendations based on the valuation of firms' fundamentals, offering these services also ultimately translates into potentially profitable trading tips. These services have come under scrutiny as the recently introduced MiFID II requires brokers to unbundle research from other services.

Our framework allows us to test whether research is actually value by investors. Table 4 presents the results where in addition to commissions, we include the number of analysts, the number of top rated analysts as ranked by Institutional Investors, and the number of buy recommendations as main explanatory variables.[1] Columns (1)-(3) present the results where each research variable is added in isolation in the regression, while Column (4) presents the multivariate version. Our results show that the average investor is willing to pay an additional 2-3bps per trade in order to have access to a top equity research analyst, while on average having access to additional analysts is worth less than 1bps. This suggests that the average investor does value research, although to a significantly less extent than execution.

V.D Value of Information

Recent studies by Barbon, Di Maggio, Franzoni, and Landier (2018) and Di Maggio, Franzoni, Kermani, and Sommavilla (2018) have shown that brokers are an important hub for order flow information, which can be strategically released to some investors in order to attract their business. We can then enrich our analysis by investigating how much order flow information is actually valued.

We measure order flow information with the broker's centrality in the network of relationships between managers and brokers. The idea being that more central brokers tend to trade with better performing investors who are themselves more likely to submit informed trades. Second, we identifies instances in which the broker has received an informed order in a particular stock and create a dummy variables for those events. Intuitively, those are instances in which it is more likely that the broker will be able to provide order flow information to other traders. Columns (1) and (2) of Table 5 provide the estimation results for the univariate case, while Column (3) reports the multivariate case. We find that investors are willing to an additional 1.5bps to trade with a more central broker. The results are even more economically significant when we consider the informed

[1] Since we only consider buy orders, these are likely to be affected only by buy recommendations.

broker measure. We find that the value of trading with an informed broker is roughly equal to 6-7bps, so way higher than the value of research. Intuitively, the color that can be provided by brokers about current order flow is significantly more impactful than the research analysis publicly released.

V.E Value of Traders

Lastly, we are able to match the Ancerno data with information about the characteristics of the traders working for the brokers. Table 6 presents the estimation results with Column (1) focusing on the fraction of traders that engaged in misconduct, Column (2) on the log number of traders working for a broker, Column (3) on the average experience of the traders, and finally Column (4) on the distance between the location of the traders and investors. The last column presents the multivariate version. We find that investors are less likely to trade with a brokerage firm whose equity traders are involved in more client disputes and regulatory offenses. A one percentage point decrease in misconduct is worth about 1.3bps. We also find evidence that investors prefer to trade with equity traders located in the same city. The value of being within 100 miles of the broker is worth about 8-9bps. Finally, Table 7 presents very similar results once we include the different dimensions in the same specification.

VI Heterogeneity

Here, we re-estimate our broker choice model where we allow the preferences to vary across investors. Specifically we re-estimate eq. (6) where we allow an investor's preferences over commissions (α_i) and other broker characteristics (β_i and μ_{ilt}) to vary across investors. To ensure we have enough power to estimate coefficients for each investor, we restrict our attention to those 254 investors where we observe at least 1,000 observations at the investor-broker-sector-month level. Table 8 displays the corresponding estimates. We report the mean and standard deviation of the estimated distribution of investor preferences. The mean preference coefficients are in line with our baseline estimates from Section V where assume that all investors have the same preference coefficients (Table 7). The estimates also indicate that there is substantial variation across investors in terms of the value they place on the execution services offered by brokers. In the proceeding subsections we investigate the heterogeneity in terms of demand elasticity, value of research and the value of information.

VI.A Demand Elasticity

We find that elasticity of demand varies dramatically across investors. Figure 2a displays the distribution of estimated demand elasticities. The average elasticity is 0.40, but varies across investors from zero to 0.80. Even among the most price sensitive investors, demand is still relatively inelastic.

We examine how the elasticity of demand varies across various investor characteristics in the following regression specification:

$$Elasticity_l = X_{it}'\gamma + \eta_{lt} \tag{7}$$

where we control for investor characteristics in X_{it}. The vector X_{it} includes a set of dummy variables indicating or not the investor is a hedge fund, large investor (above average), high performing investor (above average), and high churn investor (above average). We also control for the number of brokers an investor trades with in X_{it}. Table 9a displays the corresponding estimates. The estimates indicate that larger investors tend to have less elastic demand while firms with more network links/trading partners tend to have more elastic demand.

VI.B Value of Research

Our estimates also indicate that investors have heterogeneous preferences over the value of research. We calculate the value each investor places on research as the $Value\,of\,Research_l = \beta_{research,i}/\alpha_i$, which tells us how much value the investor places on research in terms of basis points. We focus our analysis on the value investors place on top research analysts. Figure 2b displays the distribution of values investors place on a top research analyst. The average investors is willing to pay an additional 3bps to trade with a top research analyst. However, the estimates suggest that roughly one-third of investors place essentially no value on top research analysts. This has potentially important implications for unbundling of services provided by brokers. Currently, brokers typically provided a bundled product to investors, where they bundle execution, research, and other brokerage services into one package. The results displayed in Figure 2b indicate that bundling may lead to an inefficient over-production of sell-side research as many investors are effectively force to purchase research that they do not value.

We examine how investor's preferences over research varies across various investor characteristics in the following regression specification:

$$\beta_{Research,i} = X_{it}'\gamma + \eta_{lt} \tag{8}$$

where we again control for investor characteristics in X_{it}. Table 9b displays the corresponding regression estimates. We find that hedge funds place less almost no value on sell-side research. Conversely, large investors place as about twice as much weight on research relative to the average investor. We also find evidence suggesting that better performing investors tend to place less value on sell-side research.

VI.C Value of Information

We also find that investors place different values on the information produced by brokers. We calculate the value each investor places on an trading with an informed trader as $Value\,of\,Information_l = \beta_{Informed,i}/\alpha_i$, which tells us how much the more an investor is willing to pay in order to trade with an informed brokers. Figure 2c displays the distribution of values investors place on information. The average investors is willing to pay an additional 14 bps to trade with an informed broker.

We examine how the value investors place on information varies across investors in the following regression specification:

$$\beta_{Informed,i} = X_{it}'\gamma + \eta_{lt} \tag{9}$$

where we again control for investor characteristics in X_{it}. Table 9c displays the corresponding regression estimates. Our estimate suggest that hedge funds place a larger value on order flow information, putting about 5x as much weight on that characteristic relative to other investors when choosing a broker. Conversely, large investors place a lower value on order flow information.

VII Counterfactuals

Our quantitative model also yields insight into the structure of the broker-investor network and allows us to quantify frictions in the network. Here we use our model to estimate the costs of forming a new link in the network and trading with a new counterparty.

Building on our framework from Section II, an investor's expected profits of trading through the broker in her network $\mathcal{L} = \{1, 2, ...n\}$ that maximizes her profits is

$$E[\pi_{ijkt}|\mathcal{L}] = \frac{\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i c_{ikmt} + X_{kmt}'\beta_i + \xi_{kmt}\right)\right) + \mathcal{C}}{\alpha_i}$$

where $\mathcal{C}$ is the Euler-Mascheroni constant. We consider the following hypothetical experiment to place a lower bound on the cost of establishing a link with a new trading partner. Suppose that an investor forms a link with a new trading partner such that the size of the investor's network increases from $\mathcal{L} = \{1, 2, ...n\}$to $\mathcal{L}_+\{1, 2, ...n, n+1\}$. As a result of the network expansion, the investor's expected trading costs fall by $E[\pi_{ijkt}|\mathcal{L}_+] - E[\pi_{ijkt}|\mathcal{L}] \geq 0$. It must be that the cost of forming a new network link F, is greater than the expected benefit

$$F > \frac{\ln\left(\sum_{m\in\mathcal{L}_+} \exp\left(-\alpha_i c_{ikmt} + X_{kmt}'\beta_i + \xi_{kmt}\right)\right) - \ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i c_{ikmt} + X_{kmt}'\beta_i + \xi_{kmt}\right)\right)}{\alpha_i}$$

Empirically, we consider the experiment of adding a broker with average characteristics $\bar{c}$ and $\bar{X}$ to each investor's trading network. We compute that adding an average broker to an investor's trading network lowers the investor's expected trading costs by 2bp on average. Thus, the cost of adding a new link F must be greater than 2bps.

We also consider the experiment where we remove a broker from an investor's network to calculate an upper bound on the cost of adding a new network link F. Suppose we remove a link from an investors trading network such that the size of the investor's network decreases from $\mathcal{L} = \{1, 2, ...n\}$to $\mathcal{L}_-\{1, 2, ...n-1\}$. Revealed preference indicates that, because the investor set up the network $\mathcal{L}$, it must be the case that the expected benefits of increasing the investor's network from $\mathcal{L}_-$ to $\mathcal{L}$ are greater than the cost $E[\pi_{ijkt}|\mathcal{L}] - E[\pi_{ijkt}|\mathcal{L}_-] \geq F$. Empirically, we consider the experiment of removing an average broker, in terms of the broker's characteristics, from each investor's trading network. We find that removing the average broker from an investor's trading network increases an investor's expected trading costs by 3bps on average. Thus, our estimates indicate that the cost of adding a new link must be greater than 2bp and less than 3bps, 2bp$<F<$ 3bp.

VIII Conclusions

The choice of trading venue is a key component of traders' job description and an integral part of their strategy as it is one of the main factors affecting profitability. Such a choice has become even more important with the proliferation of different intermediaries and electronic platforms. However, given investors' concerns about the confidentiality of their trading strategies, it is not surprising that we know very little about what drives investors' choices among brokers.

This paper is a first step towards a better understanding of the value provided by different brokers to investors. Some brokers are better than others in providing best execution, while some brokers offer access to top research analysts with insights about trends in the market, while finally others seem to be more able to provide valuable order flow information. We develop and estimate an empirical model of intermediary choice to investigate investors' responsiveness to all of these different dimensions. We find that investors are relatively insensitive to commissions, but on average value research, execution, and access to information. Furthermore, they are less likely to trade with a broker whose traders have misbehaved in the past. There is also a significant heterogeneity across investors, with the most active and best performers valuing less research and more the access to order flow information. We exploit the model to analyze several counterfactuals highlighting key inefficiencies in the market that raise trading costs.

References

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman (2012): "Performance of Institutional Trading Desks: An Analysis of Persistence in Trading Costs," *The Review of Financial Studies*, 25(2), 557–598.

——— (2013): "Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis," *Journal of Financial Economics*, 108(3), 773–797.

Babus, A., and P. Kondor (2018): "Trading and information diffusion in over-the-counter markets," *Econometrica*, 86(5), 1727–1769.

Barbon, A., M. Di Maggio, F. Franzoni, and A. Landier (2018): "Brokers and order flow leakage: Evidence from fire sales," *Journal of Finance*, forthcoming.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile prices in market equilibrium," *Econometrica*, pp. 841–890.

Berry, S. T. (1994): "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics*, pp. 242–262.

Chung, J.-W., and B. U. Kang (2016): "Prime broker-level comovement in hedge fund returns: information or contagion?," *Review of Financial Studies*, 29(12), 3321–3353.

Di Maggio, M., F. Franzoni, A. Kermani, and C. Sommavilla (2018): "The relevance of broker networks for information diffusion in the stock market," *Journal of Financial Economics*, forthcoming.

Duffie, D., S. Malamud, and G. Manso (2015): "Information percolation in segmented markets," *Journal of Economic Theory*, 158, 838–869.

Duffie, D., and G. Manso (2007): "Information percolation in large markets," *American Economic Review*, 97(2), 203–209.

Egan, M., A. Hortaçsu, and G. Matvos (2017): "Deposit competition and financial fragility: Evidence from the us banking sector," *American Economic Review*, 107(1), 169–216.

Glode, V., and C. Opp (2016): "Asymmetric information and intermediation chains," *American Economic Review*, 106(9), 2699–2721.

Goldstein, M. A., P. Irvine, E. Kandel, and Z. Wiener (2009): "Brokerage commissions and institutional trading patterns," *Review of Financial Studies*, 22(12), 5175–5212.

Hu, G., K. M. Jo, Y. A. Wang, and J. Xie (2018): "Institutional trading and Abel Noser data," *Journal of Corporate Finance*, 52, 143–167.

Irvine, P., M. Lipson, and A. Puckett (2006): "Tipping," *The Review of Financial Studies*, 20(3), 741–768.

Li, F. W., A. Mukherjee, and R. Sen (2017): "Inside brokers," HKUST Working Paper.

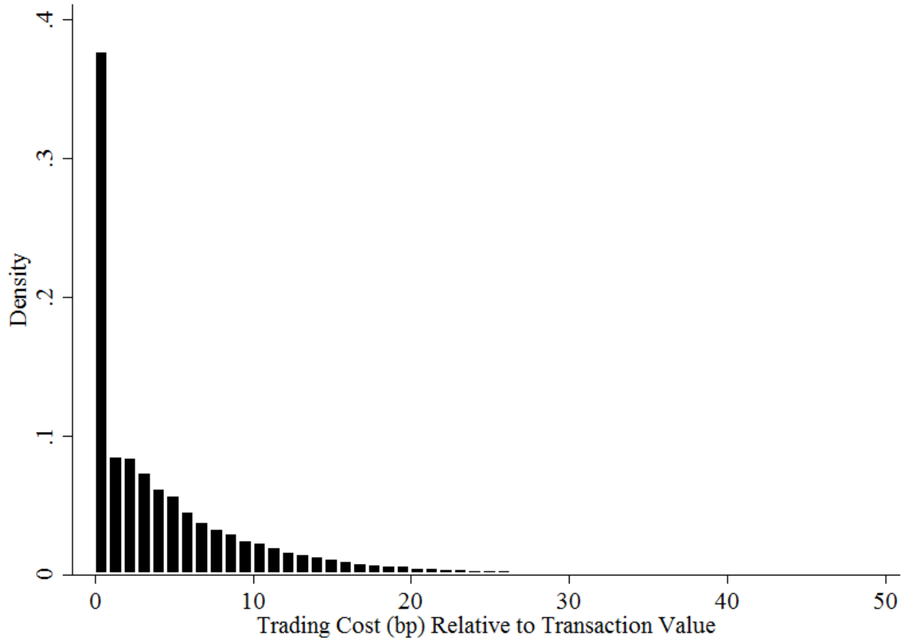
McNally, W. J., A. Shkilko, and B. F. Smith (2015): "Do brokers of insiders tip other clients?," *Management Science*, 63(2), 317–332.

Puckett, A., and X. Yan (2011): "The interim trading skills of institutional investors," *The Journal of Finance*, 66(2), 601–633.

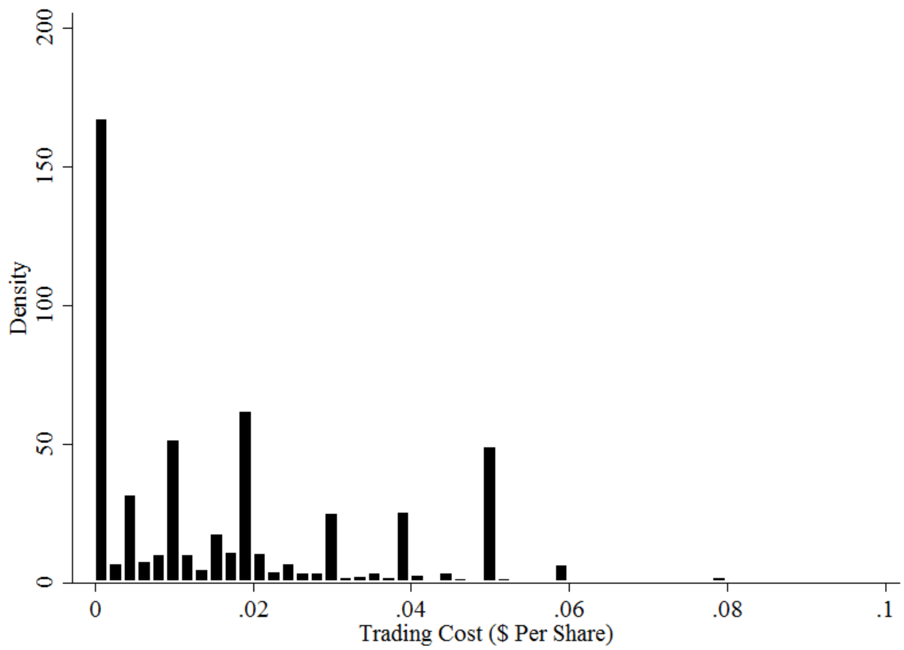
Townsend, R. M. (1978): "Intermediation with Costly Bilateral Exchange," *The Review of Economic Studies*, 45(3), 417–425.

Figure 1: Brokerage Commissions

(a) Commissions (% of Transaction Value)



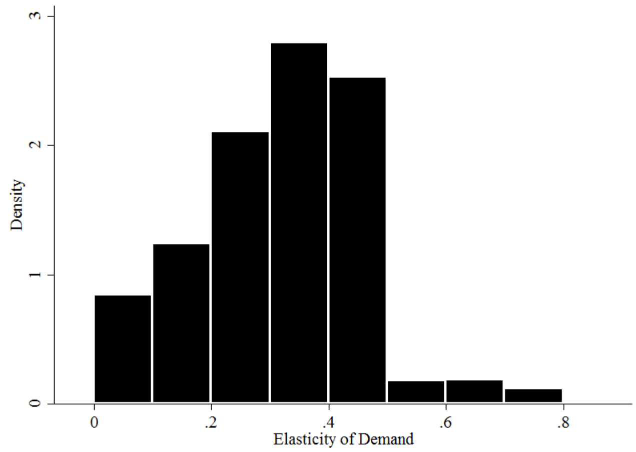
(b) Commissions ($ per Share)



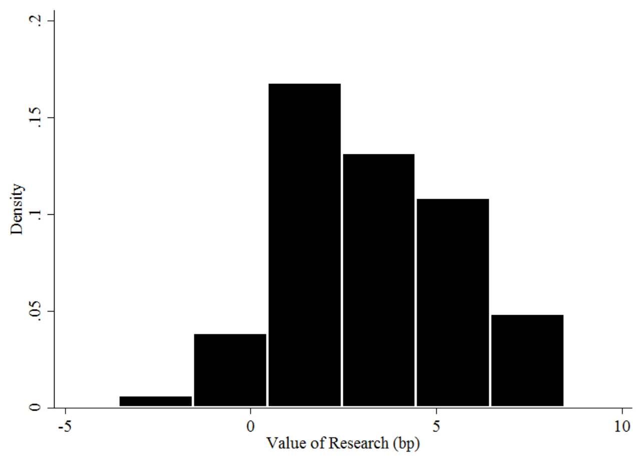
Note: Figures 1 displays the distribution of commissions charged by brokerage firms in terms of the cost relative to the value of the tranaction and the cost in terrms of dollars per share.

Figure 2: Preference Heterogeneity

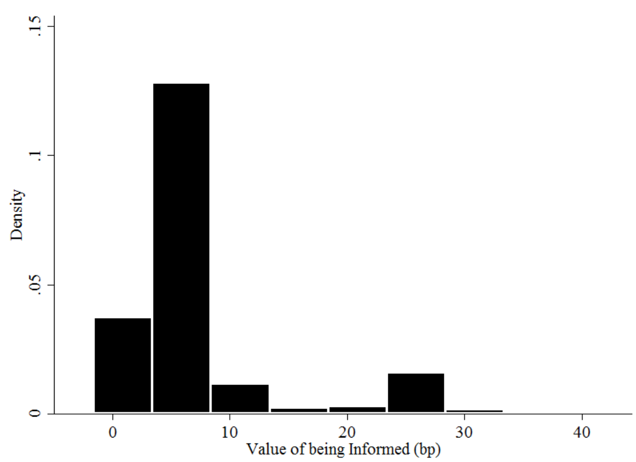
(a) Elasticity of Demand



(b) Value of a Top Research Analyst (bp)



(c) Value of Information (bp)



Note: Figure 2 panels (a)-(c) display the estimated distributions of demand elasticities, value placed on research, and value placed on information across investors. The distributions correspond to the estimates reported in Table 8.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Commissions($ per share)	6,276,744	0.03	0.12
Commissions (%)	6,276,744	0.11%	0.060%
Price Impact:			
Rel. to Px at Order:	5,895,414	0.47%	0.61%
Rel. to Opening Px:	5,897,993	0.70%	0.82%
Rel. to Px at Mgr First Order:	5,896,439	0.57%	0.70%
Research Analyts:			
Number of Analysts	6,276,744	1.49	2.45
Number of Top Analysts	6,276,744	0.16	0.47
Number of Buy Recommendations	6,276,744	0.91	2.10
Broker Information:			
Eigenvector Centrality	5,715,712	0.11	0.06
Informed Broker (Barbon et al. 2018)	6,276,744	33.33%	47.14%
Equity Traders:			
Number of Traders	2,780,668	268.361	240.8634
Experience	2,780,668	11.65	2.80
Pct of Traders Receiving Misconduct Disclosures	2,780,668	0.21%	0.68%
Distance (miles)	1,628,968	652.30	794.92
Close Distance (>100 miles)	1,628,968	33%	47%

Note: Table 1 displays the summary statistics corresponding to our data set. Observations are at the investor by month by sector by broker level.

Table 2: Broker Choice - Commission Sensitivity

	(1)	(2)	(3)
Commissions	-370***	-333***	-340***
	(14.0)	(8.78)	(9.29)
Sector×Investor×Time Fixed Effects	X	X	X
Broker Fixed Effects		X	
Broker ×Time Fixed Effects			X
IV	X	X	X
Observations	6,144,226	6,144,064	6,132,123
Mean Elasticity	0.36	0.32	0.33

Note: Table 2 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. We measure commissions in percentage terms relative to the value of the transaction. Because of the potential endogeneity of commissions, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Broker Choice: Value of Execution

	(1)	(2)	(3)	(4)	(5)	(6)
Price Impact:						
Rel. to Px at Order:	-1.29***	-69.4***				
	(0.25)	(8.18)				
Rel. to Opening Px:			-1.31***	-62.8***		
			(0.18)	(8.86)		
Rel. to Px at Mgr First Order:					-0.10	-56.64***
					(0.19)	(8.96)
Commissions	-336***	-389***	-336***	-386***	-336***	-313***
	(5.52)	(8.39)	(5.52)	(8.69)	(5.51)	(8.45)
Sector×Investor×Time Fixed Effects	X	X	X	X	X	X
Broker ×Time Fixed Effects	X	X	X	X	X	X
IV (Commissons)	X	X	X	X	X	X
IV (Price Impact)		X		X		X
Observations	5,750,996	2,860,297	5,753,583	2,862,407	5,750,979	2,860,293

Table 3 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. We measure commissions in percentage terms relative to the value of the transaction. Because of the potential endogeneity of commissions, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Price Impact is measured as the execution price relative to the benchmark price in percentage terms $\left(\frac{ExecutionPx - BenchmarkPx}{BenchmarkPx}\right)$. We use three different benchmark prices: the price at the time of the order, the opening price, and the price at the manager's first order. To account for measurement error, we also instrument for Price Impact using lagged Price Impact. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Broker Choice: Value of Research

	(1)	(2)	(3)	(4)
Research:				
Number of Analysts	0.042***			0.032***
	(0.0026)			(0.0025)
Number of Top Rated Analysts		0.099***		0.070***
		(0.0090)		(0.0092)
Number of Buy Recommendations			0.031***	0.012***
			(0.0019)	(0.0014)
Commissions	-340***	-340***	-340***	-340***
	(9.29)	(9.29)	(9.29)	(9.29)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker ×Time Fixed Effects	X	X	X	X
IV	X	X	X	X
Observations	6,132,123	6,132,123	6,132,123	6,132,123
Value of Research:				
Value of an Additional Analyst (bp)	1.24			0.94
Value of an Additional Top Analyst (bp)		2.91		2.06
Value of an Additional Buy Rec. (bp)			0.91	0.35

Note: Table 4 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. We measure commissions in percentage terms relative to the value of the transaction. Because of the potential endogeneity of commissions, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Number of top analysts is measured as the number of analysts employed by a broker in a given year that are ranked in Institutional Investor. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Broker Choice: Value of Information

	(1)	(2)	(3)
Information:			
Eigenvector Centrality	0.048***		0.049***
	(0.0063)		(0.0061)
Informed Broker (Barbon et al. 2018)		0.21***	0.23***
		(0.017)	(0.0049)
Commissions	-337***	-340***	-336***
	(5.58)	(9.28)	(5.57)
Market×Time Fixed Effects	X	X	X
Broker ×Time Fixed Effects	X	X	X
IV	X	X	X
Obervations	5,578,083	6,132,123	5,578,083
Value of Information:			
Value of 1σ Increase in Eigenvector Centrality (bp)	1.42		1.46
Value of an Informed Broker (bp)		6.18	6.85

Note: Table 5 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. We measure commissions in percentage terms relative to the value of the transaction. Because of the potential endogeneity of commissions, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Eigenvector Centrality measures the centrality of the broker at the month by sector level, where we first condition/residualize Eignvector Centrality based on the number of links the broker has in the sector. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Broker Choice: Value of Traders

	(1)	(2)	(3)	(4)	(5)
Trader Characteristics:					
Traders with Misconduct (%)	-5.30***				-2.38
	(1.57)				(1.51)
ln(Number of Traders)		0.093			-0.062
		(0.067)			(0.066)
Avg. Trader Experience			0.013		0.012
			(0.013)		(0.019)
Distance (Less than 100 mi)				0.29***	0.28***
				(0.053)	(0.064)
Commission	-389***	-389***	-389***	-314***	-347***
	(10.7)	(10.7)	(10.7)	(9.91)	(14.6)
Sector×Investor×Time Fixed Effects	X	X	X	X	X
Broker Fixed Effects	X	X	X	X	X
Other Controls					X
IV	X	X	X	X	X
Obervations	2,699,984	2,699,984	2,699,984	1,567,229	1,032,772
Value of Traders:					
Value of 1pp Decrease in Misconduct (bp)	1.36				0.69
Value of 1% Inc. In Number of Traders (bp)		0.24			-0.01
Value of 1 Year Inc. in Avg. Trader Exp. (bp)			0.33		0.34
Value of Being within 100 mi				9.24	8.07

Note: Table 6 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. Each independent variable is described in detail in Section IV.B. We measure commissions in percentage terms relative to the value of the transaction. Because of the potential endogeneity of commissions, we instrument for commissions using the average commission charged by the broker in dollar terms divided by the share price of the stock. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Broker Choice

	(1)	(2)	(3)
Commissions	-295***	-329***	-337***
	(7.22)	(5.72)	(5.65)
Price Impact:	-7.13***	-2.14***	-0.69***
	(0.56)	(0.35)	(0.25)
Research			
Number of Analysts	0.046***	0.028***	0.031***
	(0.0042)	(0.0028)	(0.0018)
Number of Top Rated Analysts	0.15***	0.066***	0.060***
	(0.014)	(0.0069)	(0.0044)
Number of Buy Recommendations	0.0049**	0.010***	0.010***
	(0.0019)	(0.0013)	(0.0011)
Information:			
Eigenvector Centrality	0.10***	0.052***	0.047***
	(0.011)	(0.0074)	(0.0056)
Informed Broker (Barbon et al. 2018)	0.40***	0.24***	0.21***
	(0.016)	(0.0084)	(0.0046)
Sector×Investor×Time Fixed Effects	X	X	X
Broker Fixed Effects		X	
Broker ×Time Fixed Effects			X
IV (Commissons)	X	X	X
Obervations	5,547,931	5,547,848	5,539,559
Mean Elasticity	0.28	0.32	0.33
Value of Research:			
Value of an Additional Analyst (bp)	1.56	0.85	0.92
Value of an Additional Top Analyst (bp)	5.08	2.01	1.78
Value of an Additional Buy Rec. (bp)	0.17	0.30	0.30
Value of Information:			
Value of 1σ Increase in Eigenvector Centrality (bp)	3.39	1.58	1.39
Value of an Informed Broker (bp)	13.56	7.29	6.23

Note: Table 7 displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. Each independent variable is described in detail in Section IV.B. We measure commissions in percentage terms relative to the value of the transaction. Standard errors are clustered at the broker by year level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Broker Choice - Heterogeneous Coefficients

	Mean	Std. Dev.
Commissions	-399***	247***
Price Impact:	-4.61***	10.25***
Research		
Number of Analysts	0.039***	0.030***
Number of Top Rated Analysts	0.11***	0.073***
Number of Buy Recommendations	0.012***	0.011***
Information:		
Eigenvector Centrality	0.0017	0.054***
Informed Broker (Barbon et al. 2018)	0.27***	0.29***
Elasticity	0.40	0.41
Value of Research:		
Value of an Additional Analyst (bp)	1.30	4.57
Value of an Additional Top Analyst (bp)	2.95	11.49
Value of an Additional Buy Rec. (bp)	0.39	2.34
Value of Information:		
Value of 1σ Increase in Eigenvector Centrality (bp) 0.30	10.01	
Value of an Informed Broker (bp)	13.86	48.27
Sector$\times$Investor$\times$Time Fixed Effects	X	
Broker$\times$Investor Fixed Effects	X	
IV (Commissons)	X	
Obervations	5,497,917	

Note: Table 8 displays the estimation results corresponding to our heterogenous coefficient discrete choice broker model (eq. 6). The unit of observation is at the manager by broker by month by sector (6-digit GICS) over the period 1999-2014. Here, we allow preferences to vary across investors. Consequently, we report the mean and standard deviation of preferences across the investors in our sample. To control for outliers, we report the estimated coefficients winsorized at the 1% level. Each independent variable is described in detail in Section IV.B. We measure commissions in percentage terms relative to the value of the transaction. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Investor Heterogeniety

(a) Elasticity of Demand

	(1)	(2)	(3)	(4)	(5)	(6)
Hedge Fund	98.6					158
	(64.1)					(99.1)
Big Investor		48.1				-53.8*
		(76.2)				(32.5)
High Performance			26.1			-4.51
			(22.4)			(19.8)
High Churn				2.75		-36.8
				(75.6)		(49.9)
Network Links					0.27	0.87*
					(0.24)	(0.51)
Observations	1,846	1,869	1,869	1,869	1,869	1,846
R-squared	0.008	0.004	0.001	0.000	0.023	0.073

(b) Value of Research

	(1)	(2)	(3)	(4)	(5)	(6)
Hedge Fund	-0.076***					-0.042***
	(0.015)					(0.014)
Big Investor		0.089***				0.031**
		(0.014)				(0.013)
High Performance			0.0100			-0.014***
			(0.015)			(0.0046)
High Churn				0.056***		0.011
				(0.015)		(0.0085)
Network Links					0.00023***	0.00027***
					(0.000051)	(0.000057)
Observations	1,846	1,869	1,869	1,869	1,869	1,846
R-squared	0.117	0.280	0.003	0.109	0.354	0.447

(c) Value of Information

	(1)	(2)	(3)	(4)	(5)	(6)
Hedge Fund	0.56***					0.59***
	(0.062)					(0.057)
Big Investor		0.032				0.100***
		(0.031)				(0.024)
High Performance			0.011			-0.0088
			(0.017)			(0.0076)
High Churn				-0.016		-0.0042
				(0.027)		(0.017)
Network Links					-0.000011	0.000063
					(0.000080)	(0.000089)
Observations	1,846	1,869	1,869	1,869	1,869	1,846
R-squared	0.697	0.004	0.001	0.001	0.000	0.741

Table 9: Investor Heterogeniety (Continued)

Note: Table 9 displays the estimation results corresponding to linear regressions displayed in equations (7)-(9). The unit of observation is at the manager by year level. The dependent variable in panel (a) is the investor's sensitivity to prices, α_i, corresponding to our estimates in Table 8. The dependent variable in panel (b) is the investor's sensitivity to a top research analyst, $\beta_{i,Research}$, corresponding to our estimates in Table 8. The dependent variable in panel (c) is the investor's sensitivity to information, $\beta_{i,Informed}$, corresponding to our estimates in Table 8. The variables Big Investor, High Performance, and High Churn are dummy variables indicating that the investor is above the mean in the respective categories. We measure commissions in percentage terms relative to the value of the transaction. Standard errors are clustered at the broker level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.