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THE VALUE OF INTERMEDIATION IN THE STOCK MARKET

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ABSTRACT

Brokers continue to play a critical role in intermediating institutional stock market transactions. More than half of all institutional investor order flow is still executed by high-touch (non-electronic) brokers. Despite the continued importance of brokers, we have limited information on what drives investors' choices among them. We develop and estimate an empirical model of broker choice that allows us to quantitatively examine each investor's responsiveness to execution costs and access to research and order flow information. Studying over 300 million institutional trades, we find that investor demand is relatively inelastic with respect to commissions and that investors are willing to pay a premium for access to top research analysts and order-flow information. There is substantial heterogeneity across investors. Relative to other investors, hedge funds tend to be more price insensitive, place less value on sell-side research, and place more value on order-flow information. Furthermore, using trader-level data, we find that investors are more likely to trade with traders who are located physically closer and are less likely to trade with traders that have misbehaved in the past. Lastly, we use our empirical model to investigate the unbundling of equity research and execution services related to the MiFID II regulations. While under-reporting for the average firm is relatively small (4%), we find that the bundling of execution and research allows some institutional investors to under-report management fees by up to 15%.

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I Introduction

Most institutional investors do not access equity markets directly. Rather, institutional investors rely on "high-touch" (non-electronic) broker trading, where trading orders are often placed over the phone. Even with the growth of algorithms, dark pools, and electronic trading platforms, institutional investors continue to execute the majority of their trades through "high-touch" brokers.[1] Given the development of, in principle, cheaper trading alternatives, such as direct market access, why do institutional investors continue to execute trades through brokers and how exactly are brokers creating value for investors? Brokers offer a variety of services to investors and potentially create value by providing efficient execution, market research, and order flow information. Traditionally, brokers have bundled these services into one package, and investors have paid for these services through one bundled-trading execution fee. The bundling of services makes it difficult to disentangle how brokers create value for investors. Related transparency issues have attracted the attention of the regulators and policymakers. This resulted in several recent policy interventions, such as MiFID II, which aim to hold investment managers accountable to best execution standards, and offer greater transparency around the services offered by brokers to investors.

Figure 1 displays the share of equity trades executed through high-touch brokers and the number of registered equity traders in the US over the period 2008-2017. Over the past ten years, the share of equity trades executed through high-touch brokers has remained relatively constant. The persistence of high-touch broker trades suggests that brokers continue to create value for investors, despite the perceived growth of alternative trading venues.[2] Consistent with this trend, the number of registered equity traders in the U.S. has remained relatively constant since the financial crisis (Figure 1).

Despite the role brokers play in the institutional markets, we still know little about how they create value for institutional investors. Brokers provide investors with services ranging from trade execution to research. The SEC mandates that investment managers should obtain Best Execution which the SEC describes as "a money manager should consider the full range and quality of a Broker's services in placing brokerage including, among other things, the value of research provided as well as execution capability, commission rate, financial responsibility, and responsiveness to the money manager."[3] In this paper, we examine how investors make their trade decisions in order to better understand the role of brokers in equity markets and the value that they bring to investors. Specifically, the central question is what are the key dimensions that investors trade off in making these decisions. For example, why does an institutional investor decide to execute a particular trade with Goldman Sachs rather than Morgan Stanley? Is it because Goldman Sachs is cheaper, provides better execution, or because Goldman Sachs provides better services such as research or access to

[1] [https://www.greenwich.com/equities/voice-trading] accessed 5/9/2019

[2] Our analysis focuses on high touch (non-electronic) broker trading which remains commonplace in the industry. This in contrast to the recent work examining the growth and prolifieration of high-frequency trading and their impact on market structure (e.g. Ye, Yao, and Gai (2013), Budish, Cramton, and Shim (2015) and Budish, Lee, and Shim (2019)).

[3] https://www.sec.gov/rules/interp/34-23170.pdf

order-flow information? Understanding these execution decisions provides insight into how brokers create value for institutional investors and might be instrumental in guiding policy interventions and getting insights into their potential intended and unintended effects.

A key challenge in studying these issues is a lack of data, since understanding these issues requires detailed data on brokerage firms and institutional trading patterns. Observing data on the latter is challenging due to investors' concerns about the confidentiality of their trades. We overcome this challenge using a rich micro-data set covering hundreds of millions of equity transactions with detailed information on both the institutional investors and brokerage firms involved in the 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 and includes trade-level data for institutional investors, covering 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. To measure each broker's capacities in a given market and time, 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.

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 (2019) 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 disclosures 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.

To understand how institutional investors make execution decisions, we develop an empirical model of brokerage firm choice to investigate the execution decisions of institutional investors. We examine an investor's trading decision process with a particular emphasis on *where* investors decide to execute their trade. We model an investor's execution decision as a discrete choice problem. Investors choose the broker that maximizes their expected trading profits, or put differently, the broker that minimizes their expected execution costs. When deciding among brokers, investors trade off execution costs (i.e. fees), quality of execution (i.e. price impact), and the quality of other services provided by the broker such as research and order flow information. In this sense, we estimate the intensive margin of the investor-broker network.

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 assumptions over the distribution of investor preferences. Second, a common problem in the demand estimation literature is the endogeneity of prices, or in this case transaction fees/commissions. If brokerage firms are able to flexibly adjust fees based on the actions and preferences of investors, fees will be endogenous. We are able to address the endogeneity of fees through an instrumental variables approach that exploits unique institutional features of the brokerage industry. Specifically, brokerage firms charge transaction fees in terms of cents per share traded, typically rounded to the nearest whole number. This rigidity in the way fees are set provides exogenous variation in the effective transaction fees paid by investors.

We use our framework to better understand how institutional investors trade-off fees, quality of execution, research, and order flow information when deciding where to execute trades. We first examine the price sensitivity of investors. Investors typically compensate brokerage firms for their services by executing trades through them and paying a per-share commission fee. The average trading commission fee in our data is roughly 3 cents per share or roughly 13bps relative to the value of the transaction. Our broker choice estimates suggest that the majority of institutional investors are relatively price insensitive. The average demand elasticity in our data set is roughly 0.47. The estimates imply that if a broker increases the fee it charges by 1%, its trading volumes will go down by an associated 0.47%. In other words, the estimates suggest that investor-broker relationships are "sticky" and that there are potentially many other factors that influence broker choice.

An important factor driving an investor's trading decision is the quality of execution, which represents an implicit dimension of trading costs. Traders may differ in their ability to execute large trade 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 the price of the stock at the placement of the investor's order. We find that a one standard deviation improvement in execution is worth 7bps, which is equal to roughly one-half of a standard deviation in brokerage fees.

Brokers also offer research to their clients, employing equity analysts who provide forecasts, research reports, and general expertise in a given sector. We test whether investors value this broker provided "sell-side" research when executing trades. Brokers have traditionally bundled these research services with their trade execution such that investors pay one bundled execution fee for all of the services a broker offers. Our estimates indicate that investors are willing to pay 1-2 bps (relative to the value of the transaction) to have access to a research analyst and an additional

2-4bps to have access to a top analyst in the sector (as per Institutional Investor). In other words, the average investor would be willing to pay up to a roughly 50% higher trading commission fee in order to have access to a top analyst.

We enrich our analysis by investigating whether brokers are considered a valuable source of order flow information. We measure order flow information in two ways. First, following Di Maggio, Franzoni, Kermani, and Sommavilla (2018) we define a broker as being informed if he has traded with an informed investor. We find that investors are willing to pay an additional 2-6bps (relative to the value of the transaction) 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. As is standard in the literature, we measure a broker's centrality within the network based on its eigenvector centrality. We find that investors are willing to pay an additional 1-3bps (relative to the value of the transaction) to trade with a broker that is more centrally located within the broker network by one standard deviation.

A unique feature of our data set is that we not only observe the brokerage firm involved in a transaction, but we also have data on the individual traders employed by the corresponding brokerage firm. 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. Roughly 6.5% of the traders in our sample have a past record of misconduct which includes customer disputes resulting in a settlement and regulatory offenses.[4] Our results indicate that a one percentage point increase in the number of traders engaging in misconduct (roughly one additional trader for the median brokerage firm) is associated with a 2% decline in the brokerage firm's transaction volumes.[5] The results suggest that the malfeasance of one trader can have a big impact on a firm's reputation and trading volumes. Investors also value those traders with more experience and are willing to pay roughly an additional 1bp (relative to the value of the transaction more) per additional year of trader experience. Lastly, we find evidence that investors prefer to trade with equity traders located in the same city as the investor. Even though the equity orders are placed either electronically or over the phone, physical proximity to the broker influences an investor's trading decision. This is consistent with the idea that "trading is—and always has been—a relationship business."[6]

Our rich setting also allows us 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 also find that roughly one-third of investors place no value on sell-side research. Hedge funds, as opposed to mutual funds, are among those investors who place a lower value on sell-side research. Conversely, hedge funds appear to place a premium on the other types of information produced

[4]Following Egan, Matvos, and Seru (2019) we define misconduct as any customer dispute that resulted in a settlement, regulatory offenses, criminal offenses, and cases where the trader was fired for cause.

[5]A one percentage point increase in misconduct corresponds $-2.18 \times (1 - s)$ percent decrease in the broker's transaction volumes where s is the broker's current market share (Table 3). We calculate the marginal effect using the average market share in our sample ($s = 10\%$).

[6]The quote is from Johnson, Vice President of Market Structure and Technology at Greenwich Associates. [https://www.bloomberg.com/professional/blog/human-high-touch-trading-stay/] accessed 5/9/2019.

brokerage firms, such as whether or not the broker has access to informed order flow.

Lastly, we use our estimates to explore the effects of unbundling in the industry. While the brokerage firms have traditionally bundled their services, the industry has slowly moved away from bundling over the last fifteen years . As part of recent changes in regulations, European regulators mandate that brokers must unbundle their services as part of MiFID II. The impetus behind unbundling and MiFID II is to limit the use of "soft-dollars" and improve market transparency. With bundling, investors pay for research services with soft-dollars through trading commission revenues, rather than paying for them directly (hard-dollars). The concern with soft-dollar payments is that they are borne by the end-investor and are not disclosed by the fund. Hence, paying for research with soft-dollars results in investment managers under-reporting fund management fees. We use our framework to estimate the value of soft-dollars used to obtain research from brokers. Specifically, for each investor, we separately calculate the investor's shadow-value of broker-produced sell-side research following the methodology used in Petrin (2002).[7] While the shadow value of research-related soft-dollars is small for the average investor (4% of management fees), there is substantial heterogeneity across firms; our estimates suggest that the use of soft-dollars allows firms to under-report management fees by up to 15%.

I.A Related Literature

The paper relates to different strands of the literature in finance and industrial organization. We use standard tools from the industrial organization literature to understand how institutional investors trade and how brokers create value for investors. These same tools provide insight into the structure of brokerage markets and allow us to quantitatively address counterfactuals related to the unbundling of brokerage services.

Methodologically, we develop and estimate a framework for understanding an investor's demand for brokerage services using a standard demand model in the industrial organization literature (Berry (1994), Berry, Levinsohn, and Pakes (1995)). This methodology has been used in other financial applications such as demand for bank deposits (Dick (2008); Egan, Hortaçsu, and Matvos (2017); Egan, Lewellen, and Sunderam (2017); Wang, Whited, Wu, and Xiao (2018); and Xiao (2019)), bonds (Egan (2019)), annuities (Koijen and Yogo (2016)), and credit default swaps (Du, Gadgil, Gordy, and Vega (2019)). An advantage in our setting is that we observe each investor make thousands of trades, which allows us to estimate demand for brokerage services at the individual investor-level. Furthermore, due to institutional features of the market, prices are set in a quasi-exogenous manner in terms of cents per share traded. These two features make the brokerage market an ideal application for these demand estimation tools. This framework allows us to quantify how

[7] Soft-dollars broadly refers to two-related but distinct types different types of transactions: in-house and third-party. The first and most common type involves in-house transactions. Specifically, the investment manager pays for research and brokerage services obtained from a broker by directly compensating that broker with trading commissions. Second, an investment manager could compensate a third party research provider by paying a particular brokerage firm with trading commissions and having that brokerage firm direct a portion of those fees to the third party research provider.

brokers create value of institutional clients along different dimensions.

Our work draws inspiration from recent papers that highlight the role of financial intermediaries in creating value through information production. In particular, Babus and Kondor (2018) model the trading behavior of privately-informed dealers in OTC markets. We differ from this paper by focusing on a centralized market, the stock market. The brokers that we study only convey their client's trades to the market, and do not take positions using their inventory. However, we build on the authors' intuition that intermediaries are able to achieve an informational advantage by finding that the clients of these intermediaries stand to 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).

The paper also builds on the empirical literature on brokerage services and institutional trading patterns. 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 and find evidence suggesting that broker-provided services play a key role in these relationships. 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 contribution is to develop and estimate a framework for understanding and quantifying how brokers create value for institutional clients, using novel and detailed trade- and individual-level data.

Our paper also relates to the work on the role of sell-side research analysts and the value they create for investors. There is a broad literature documenting the value of trading on analyst recommendations including but not limited to Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Barber, Lehavy, McNichols, and Trueman (2003), Jegadeesh, Kim, Krische, and Lee (2004), Birru, Gokkaya, Liu, and Stulz (2019), and Bharath and Bonini (2019). Womack (1996) finds that stock prices positively respond to buy recommendations and drop for sell recommendations, concluding that analysts produce "valuable information for which a brokerage firm should be compensated" (p139). Womack (1996) also documents increased trading volume in response to analyst recommendations. Birru, Gokkaya, Liu, and Stulz (2019) focus particularly on analyst trade ideas and show that analyst trade ideas earn significant abnormal returns. In contrast to much of the previous literature, we examine the value of sell-side research using the revealed preferences of institutional investors, the consumers of sell-side research. In line with the previous literature, we find that analysts produce valuable information and using our structural model, quantify the premium that investors attach to that research. In particular, we uncover significant heterogeneity in the premium that investors are willing to pay for information and highlight that the venue-routing decision is a multidimensional one, where order flow information, misconduct, and market impact all play a significant role. We also find evidence that investors place a premium on the top analysts ranked in Institutional Investor which is consistent with the finding that these top rated analysts provide more accurate forecasts (Stickel (1992)).

We use our empirical estimates to understand the effects of unbundling and quantify the shadow-value of sell-side research consumed by each investor in order to assess the magnitude of soft-dollars in the industry. There is a long theoretical literature on bundling dating back to Stigler (1963) and Adams and Yellen (1976), but the empirical evidence is relatively limited. Previous work has documented the impact of bundling in television markets (Crawford and Yurukoglu (2012)) and other media markets (Shiller and Waldfogel (2011) and Ho, Ho, and Mortimer (2012)). In these settings, the motivation for unbundling comes from the firm side as it is used as a way of price discriminating across consumers. In sharp contrast, bundling in brokerage markets is partially demand-driven. Investors may prefer to pay for brokerage services with soft-dollar bundled commissions rather than hard dollars for transparency reasons.

Blume (1993) provides an overview of soft-dollars in the brokerage industry and survey evidence on how soft-dollars impact the structure of the industry. Soft-dollars broadly refer to two related but distinct types of transactions: in-house and third-party. In the most common transaction type, in-house transactions (Blume (1993)), the investment manager directly compensates a brokerage firm with trading commissions for research and other services the brokerage firm provides to the investor or the investor's clients. This is a contrast to third-party transactions, in which the broker providing execution redirects a portion of the trading commissions to a third-party research provider.[8] Our analysis focuses on the former and more common in-house related soft-dollar payments. Using propriety data, Conrad, Johnson, and Wahal (2001) provides the first estimates on the costs of third-party soft-dollar arrangements on a trade-by-trade basis. Conrad, Johnson, and Wahal (2001) identifies a set of third-party soft-dollar brokers and examines how the transaction costs associated with those third-party soft-dollar brokers compares with other brokerage firms. Conrad, Johnson, and Wahal (2001) estimates that the costs of third party soft-dollar transactions are roughly 10-13bp over the period 1994-1996. While we focus on in-house soft-dollars instead of third party soft-dollar arrangements, we find similar costs/magnitudes as in Conrad, Johnson, and Wahal (2001).

[8]For example, suppose an investment manager would like access to the research produced by a third-party firm XYZ Research Inc. Rather than paying XYZ Research Inc. directly, the investment manager could arrange to compensate XYZ Research Inc. by trading with a particular brokerage firm and having that brokerage firm pass a predetermined portion of the fees to XZY Research Inc.

II Framework: Institutional Demand for Brokerage Services

II.A Institutional Demand for Brokerage Services

We develop an empirical model of broker choice. Specifically, we examine an investor's decision regarding *where* to execute their trade, conditional on the investor's initial decision to trade a specific security. 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 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 expected 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:[9]

$$E[u_{ijklt}] = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt} + \epsilon_{ijklt} \tag{1}$$

Investors pay an investor-broker-sector specific f_{iklt} fee for executing a trade with broker l, from which she derives dis-utility $-\alpha_i f_{iklt}$. The parameter $\alpha_i > 0$ measures the investor's sensitivity to brokerage fees. 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 $X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt} + \epsilon_{ijklt}$. 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 Sachs 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 provided by the brokerage firms. Arguably, investors allocate trades to brokers taking into consideration the research services that the investor can receive from the broker once a stable relationship is established. For example, Goldman Sachs may offer better research coverage or be privy to better information regarding stocks in the technology sector than Goldman Sach's competitors. An investor may decide to do business with Goldman Sach internalizing the research and trading tips that this relationship can bring. 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.

Brokerage firms may differ in their quality of services along other dimensions beyond those captured in X_{klt}. For example, some brokerage firms may have access to their own proprietary dark

[9] We focus on an investor's expected utility of trading with a particular broker because the investor may not perfectly observe all of the relevant characteristics, such as realized price impact, prior to when the trade is executed.

pools and/or have better technology. The term μ_{ilt} is an investor-by-broker-by-time fixed effect that captures these broad differences in technology across brokerage firms. Note that this broker fixed effect (μ_{ilt}) varies across time to capture broker-specific changes in technology (i.e. the addition of a dark pool or changes in dark pool liquidity) and varies across investors to capture investor-specific preferences over these broker differences.

The term ξ_{iklt} is a time varying investor-by-broker-by-sector latent variable that measures a brokerage firm's execution services in ways not captured by X_{klt} or μ_{ilt}. For example, Goldman Sach's ability to efficiently trade a stock may vary over time in a way that is not captured in the vector X_{klt} or μ_{ilt}. Lastly, the variable ϵ_{ijklt} reflects an investor-by-trade-by-broker-by-sector-by-time, latent, 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 term ϵ_{ijklt} also potentially captures an investor's time-varying expectations about the quality of services a broker offers not captured in the vector X_{klt}. 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. We can therefore write an investor $i's$ expected indirect utility of executing trade idea j at in sector k with broker l at time t in terms of the trade-specific (ϵ_{ijkt}) and non-trade-specific, average, utility component $(\overline{u}_{iklt})$:

$$E[u_{ijklt}] = \overline{u}_{iklt} + \epsilon_{ijklt}$$

where $\overline{u}_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt}$.

While we present our framework in terms of an investor's utility, our framework nests, but is not limited to, the case where investors only derive utility from expected profits. Under the scenario where investors only drive 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

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

The vector β_i/α_i captures how the various services offered by a brokerage firm translate into an investor's profits. For example, the coefficient corresponding to research, $\beta_i^{Research}/\alpha_i$, tells us how investors value research services offered by brokerage firms in terms of expected future profits. Although our framework nests the case where investors only care about expected profits, our framework and subsequent estimation strategy is more general, and we do not have to take a stance on underlying factors driving investor preferences.

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

$$\max_{l \in \mathcal{L}} E[u_{ijklt}] \tag{3}$$

Under the assumption that the investor-by-trade-by-broker-by-sector-by-time specific profit shock, ϵ_{ijklt}, 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

$$\Pr(l) = \frac{\exp\left(-\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt}\right)}{\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)} \tag{4}$$

The above likelihood corresponds to the multinomial logit distribution and is the core of our estimation strategy below. It is straightforward to flexibly estimate our demand framework, and the framework allows us to directly and precisely measure how institutional investors trade-off and value broker-provided services. The details are given in Section IV.

Lastly, while we introduced our framework in the contextof an investor's decision regarding where to execute her trade *conditional* on the investor's initial decision to trade a specific security, our framework and corresponding estimates also generalize to the setting where brokers influence an investor's initial decision of whether or not to trade. One might think that the services offered by a brokerage firm and the expected profits of trading with a particular brokerage firm could induce an investment manager to make additional trades. For example, broker research could motivate an investor to trade. In our baseline framework, an investor needs to trade a security and chooses among n brokers to execute the trade with. Without any loss in generality, one could recast our model to include, in addition to choosing where to trade a security among n brokers, the outside option of not trading the particular security (which can also be influenced by the broker). As discussed below in our estimation section, adding the outside option of not trading produces numerically equivalent estimation results.

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. We restrict our attention to those observations where we observe complete trade information (parties involved, security, date, and commission) where the investor reported paying a commission fee to the broker.[10]

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

[10] We drop observations where the investor does not report paying a positive commission fee to the broker. We drop these trades because we do not observe whether these zero fee trades are indeed zero fee trades or simply observations with missing fee data. In untabulated results we re-estimate our baseline demand specifications where we include these trades and find comparable estimates.

performance, suggesting that the data should not suffer from self-reporting bias. Second, 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 fiduciary obligations 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 ticker-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 Ancerno 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 firm's 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.[11] 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 1.47 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 brokerage firm in our sample employs 0.16 top analysts in a given sector and year. Previous work has shown that these top analysts provide more accurate forecasts (Stickel (1992)). Evidence from the brokerage

[11] We merge the I/B/E/S analyst data to the brokerage firm names using data from FINRA's BrokerCheck website and a leading social networking website. As described below, FINRA's BrokerCheck data provides data, including the employment history, on the universe of individuals registered in the securities industry, including equity research analysts.

industry indicates that these type of industry polls are critical for the evaluation and careers of research analysts (Groysberg and Healy (2013)). The purported policy at Lehman Brothers was for its research analysts to make "Institutional Investor or die" (Nanda, Groysberg, and Prusiner (2008)). These variables help capture the quality of research services at the year-by-sector-by-brokerage firm-level.

III.C BrokerCheck Data

We also examine how execution varies with the 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 2005-2018 as described further in Egan, Matvos, and Seru (2019).

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 (Figure 1). For each trader, we observe the trader's complete employment history. The average trader in our sample has 12 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 have engaged in misconduct, where misconduct is defined as per Egan, Matvos, and Seru (2019) 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 that they trade in. Table 1 indicates that at the average brokerage firm in our sample, roughly 0.20% 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 668 miles, though 33% of our broker-investor trading pairs are within 100 miles of each other.

IV Estimation

We use the Ancerno micro transaction-level data to estimate our broker choice/demand model from Section II. The model is straightforward to take to the data and allows us to determine how investors value the services that brokerage firms provide. Our estimation procedure most closely follows Berry (1994) and Berry, Levinsohn, and Pakes (1995). However, the extensive and detailed nature of the 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 assumptions over the distribution of investor preferences α and β. To facilitate estimation, we aggregate the individual trades an investor makes based on the dollar value of the transaction (share price $\times$ quantity) at the month-by-sector-by-broker level. In other words, we define the market at the investor-by-month-by-sector level.[12]

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

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

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

$$\ln s_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt} - \ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)\right) \tag{6}$$

Notice that the non-linear term $\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)\right)$ is constant in a given market. Therefore we can estimate eq. (6) using linear regression where we include an investor-by-sector-by-time market fixed effect (μ_{ikt}) to absorb the non-linear term.[13] We estimate

[12] We define the market at the investor-by-month-by-sector level rather than at the investor-by-month-by-stock level to match how brokerage are organized. For example, sell-side research teams are typically organized at the sector level. Aggregation helps facilitate estimation and allows us to estimate the model using linear regression rather than using maximum likelihood or other non-linear estimation methods.

[13] Notice that we define market shares and the investor's choice set based on the trades investor i executes in sector k at time t. As shown in eq. (6) the market share of broker l in a given market (month-by-investor-by-sector) depends on utility investor i derives from trading with broker l $(-\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt})$ as well as the utility thatthe investor derives from trading with any other potential trading partner in his/her choice set $(\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)\right))$. When estimating eq. (6) we include an investor-by-sector-by-time fixed effect that absorbs the nonlinear term $\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)\right)$. Because the term $\ln\left(\sum_{m\in\mathcal{L}} \exp\left(-\alpha_i f_{ikmt} + X'_{kmt}\beta_i + \mu_{imt} + \xi_{ikmt}\right)\right)$ is absorbed in the fixed effect, we do not need to observe or even define an investor's full choice set. Consequently, if we were to re-estimate our model from Section II where investors have the option of not trading, our estimates would be numerically equivalent to our baseline estimates.

the linear specification

$$\ln s_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \mu_{ikt} + \xi_{iklt} \tag{7}$$

where X_{klt} is our vector of broker-by-sector-by-time characteristics and μ_{ilt} is an investor-by-broker-by-time fixed effect. We describe the construction and details of each our broker characteristics X_{klt} in the proceeding section. In our baseline specifications reported in the proceeding section (Section V), we restrict the preferences of investors to be the same across investors such that $\alpha_i = \alpha$, $\beta_i = \beta$, and $\mu_{ilt} = \mu_{lt}$. However, we relax this assumption in Section VI where we allow preferences to vary flexibly across investors.

In our main regression specifications, we include broker-by-time fixed effects (μ_{lt}). These fixed effects capture broad, potentially time-varying, differences across brokerage firms. For example, some brokerage firms may have better algorithms and/or access to different trading venues or dark pools. These differences in trading technologies across firms will be captured in our broker fixed effect.

One of the standard issues in demand estimation that we need to address is the endogeneity of fees. Fees are potentially endogenous if brokers observe demand shocks, ξ_{iklt}, prior to setting their prices. Conceptually, the idea is the following: if brokers know thattheir services are in high demand and/or anticipate high order flow, they may adjust their fees accordingly. In general, this potential endogeneity problem will bias the OLS estimates of $-\alpha$ upwards such that we would underestimate an investor's responsiveness to fees. We address the endogeneity of fees using instrumental variables as described in the proceeding section.

The reason in the demand estimation literature why researchers have specifically been more concerned about the endogeneity of prices (fees f in our setting), rather than other product characteristics (broker characteristics X in our setting), is because prices (fees) are likely to be the margin of adjustment in response to time- and sector-varying demand shocks. Other product characteristics are thought to be relatively fixed in the short run. For example, in our setting, it is unlikely that firms are adjusting their research coverage in response to time-varying demand shocks because the hiring process for research analysts is a lengthy/involved process that regularly takes a year (Groysberg and Healy (2013)).

We micro-found our demand system in Section II. Micro-founding the demand system provides additional interpretation and allows us to investigate counterfactuals in Section VII. However, it is worth noting that our estimates also have a reduced-form interpretation in addition to a structural interpretation; we are essentially regressing broker trade volumes on a vector of broker characteristics. Thus, our estimation results are more general than what our model in Section II entails.

In the proceeding section we describe each of the control variables used in our analysis and discuss some of empirical implementation issues associated with estimating eq. (6) due to endogeneity and measurement error issues.

IV.B Broker Characteristics

We are interested in the factors that drive institutional investors' execution decisions across brokers. Using our rich data set described in Section III we analyze how fees, 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 estimation.

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

$$f_{ijklt} = \frac{Total\, Fee\, in\, USD_{ijklt}}{Value\, of\, Transaction\, in\, USD_{ijklt}}$$

The average fees on a transaction is 13 points (bp). Figure 2a displays the distribution of fees paid by investors. There is substantial variation in fees paid by investors. The standard deviation of fees is 13bps and fees range from near zero to upwards of 20bps. The average mutual fund turned over 54% of its portfolio in a given year over the period 2000-2014, which suggests that the variation in trading fees could be costly on an annual basis. For the average mutual fund, a one-standard deviation increase in trading fees translates to an annualized cost of 14bp ($\approx 2 \times 54\% \times 13$bp) relative to the fund's total assets.[14] To put these numbers in perspective, the average mutual fund over that same period charged an expense ratio of 0.87% (2018 Investment Company Factbook).

As discussed above, a standard problem in this type of choice/demand problem is the endogeneity of prices/fees. If brokerage firms observe the error term ξ_{iklt} prior to setting their fees, fees would be correlated with the unobservable term ξ_{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 ξ_{iklt}. In response to the demand shock, the brokerage firm may find it optimal to increase the trading fee it charges. The endogeneity problem will cause the coefficient $-\alpha$ to be biased upwards such that the OLS estimates will indicate that 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 (see Goldstein, Irvine, Kandel, and Wiener (2009)).[15] Figure 2b displays the distribution of fees charged on a per share basis. As illustrated in the figure, the fees are bunched around the whole numbers in terms of cents per share ranging between 1 cent and 6 cents per share (the mode is 5 cents per share). However, the relevant metric for a profit maximizing investor is measuring fees in percentage terms relative to the value of a transaction. We argue that a one cent increase in the fee per share is more costly when an investor is trading a stock priced at $1 per share

[14] When calculating annual trading costs, we multiply turnover by two to account for the fact that turning over a portfolio involves both a buy and a sell trade.

[15] Stock exchanges also typically charge a fixed dollar amount per shares of stock traded (Chao, Yao, and Ye (2018)).

than when she is trading a stock priced at \$1,000 per share. Consequently, the relevant way for an investor to evaluate fees is in percentage terms.

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

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

The instrument is correlated with our measure of fees in percentage terms f_{ijklt} because, all else equal, a decrease in the share price makes the fixed per-share fee more expensive on a relative basis. As discussed in the proceeding section, our instruments yield Cragg-Donald F Statistics well in excess of 100 in each specification (Cragg and Donald (1993)). 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 ξ_{iklt}. While movement in stock prices would certainly be correlated with an investor's decision to trade, what matters for our setting is that movements in stock prices are not correlated with *who* an investor trades with at a particular moment in time. 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.

Research: We measure the level and quality of a brokerage firms research coverage in a particular sector along two 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. We examine whether investors are more likely to trade with brokers who have analyst coverage in the corresponding sector and measure the value that investors place on those sell-side analysts.

Information: Brokers may have access to different information in the market due to the structure of the market and the counterparties that the brokers deal with on a daily basis. We use two different measures to capture how informed a broker is. These measures of broker information draw inspiration from Di Maggio, Franzoni, Kermani, and Sommavilla (2018). First, we 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. investors 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. We construct eigenvector centrality at the sector-by-month-level for each investor i and broker l pair, $Eigenvector\_Centrality_{iklt}$. To avoid clear endogeneity concerns, we remove all of investor $i's$ trades from the network when computing the centrality of broker of broker l in sector k at time t, $Eigenvector\_Centrality_{iklt}$.

We also control for whether or not a broker is "informed" in a given market. Di Maggio, Franzoni, Kermani, and Sommavilla (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 these authors, we define an "informed trade" as abnormally large (75th percentile) profitable trade made by a hedge fund. Roughly 1.7% of the trades in our sample are classified as informed. In our analysis we control for whether or not the broker received an informed trade in a given month and sector, $Informed_{klt}$. To avoid simultaneity issues, we include the variable $Informed_{klt}$ lagged by one month in our analysis ($Informed_{klt-1}$).[16] This allows us to measure how informed order flow spills over to other investors.

Price Impact: Another key factor driving an investor's trade decision is the quality of execution. Traders may differ in their ability to execute large trade 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

$$Price\,Impact_{ijklt} = \left(\frac{Execution\,Price_{ijklt} - Benchmark\,Price_{ijklt}}{Benchmark\,Price_{ijklt}}\right) \times Side_{ijklt}$$

Here, we define the benchmark price as the price of the stock at the placement of the investor's order. The variable $Side_{ijkt}$ is equal to 1 if the trade is a buy trade and equal to -1 if the trade is a sell trade. All else equal, investors prefer a lower price impact, and a high price impact is indicative of worse execution.

To calculate the price impact in our data, we first calculate the weighted-average price impact at the broker-by-month-by-stock-level to construct the variable $Price\,Impact_{lst}$, where l indexes the broker, s the stock, and t the month. To account for time varying differences in the liquidity of different stocks, we residualize the variable $Price\,Impact_{lst}$ on a vector of stock-by-month fixed effects to construct the variable $Price\,Impact^{*}_{lst}$. This is similar to the way Anand, Irvine, Puckett, and Venkataraman (2012) measure trading desk performance, where they regress price impact on a vector of stock-specific characteristics. Lastly, we calculate the weighted-average of $Price\,Impact^{*}_{lst}$. at the broker-by-sector-by-month level ($Price\,Impact^{*}_{lkt}$), which corresponds to our definition of a market and is the primary observational unit of our analysis. The variable $Price\,Impact^{*}_{lkt}$ measures a broker's trading ability at the sector-by-month level.

There are three potential concerns with our price impact measure $Price\,Impact^{*}_{lkt}$. First, it is 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 suffer from 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

[16] By construction, the variable $Informed_{klt}$ indicates that one manager executed an informed trade through broker l in sector k in month t. Thus $Informed_{klt}$ will be, at least partially, mechanically related to the trades executed through a broker. Consequently, we lag $Informed$ by one month, to measure how proxy how the execution of informed order flow influences the proceeding execution decisions of other investors.

able to control for an investor's expectations about the price impact at time t, given the investor's information set at time $t-1$, $E[Price\,Impact^*_{lkt}|\mathcal{I}_{t-1}]$. Lastly, and related to the previous point, $Price\,Impact^*_{lkt}$ could suffer from reverse causality. If a broker experiences a positive demand shock in a specific sector such that a large number of investors choose to trade with the broker, this could lead to the broker providing either better or worse execution due to increased trading volumes. To address these issues we use both contemporaneous and lagged price impact as a proxies for an investor's price impact expectations:

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

$$E[Price\,Impact^*_{lkt}|\mathcal{I}_{t-1}] = \overline{Price\,Impact^*_{lkt-12}} + \nu_{ijklt}$$

where $\overline{Price\,Impact^*_{lkt-12}}$ is the lagged twelve-month rolling weighted average of broker $l's$ price impact in sector k. We then use contemporaneous price impact as a proxy for investor price impact expectations and use lagged price impact as an instrument. Previous work finds that there is strong persistence in broker trading performance (Anand, Irvine, Puckett, and Venkataraman (2012)) which indicates that our instrument will be relevant (i.e. there are systematic differences across brokers that determine their execution quality). 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.

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 that 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

Table 2 presents our main sets of estimation results corresponding to eq. (7). The columns differ with respect to the set of fixed effects and whether or not we estimate the model using ordinary least squares or instrumental variables. In column (1) we report our baseline set of results where we estimate the model using ordinary least squares and include market fixed effects. In column (2) we re-estimate our baseline model where we control for both fees and expected price impact as described in Section IV. Lastly, in columns (3) and (4) we include broker and broker×time fixed effects to capture differences in trading service quality across brokerage firms. In the proceeding subsections, we discuss and interpret how investors respond and value each of the brokerage firm characteristics.

V.A Fee Sensitivity

One of the primary coefficients of interest is how sensitive institutional investors are with respect to fees. In each column we estimate a negative and significant relationship between trading volumes and brokerage fees. As expected, the estimated effect becomes more negative once we employ instrumental variables. We would expect the OLS estimated fee coefficient to be biased upwards due to the endogeneity of fees. If brokers anticipate a positive demand shock (ξ_{iklt}), they will find it optimal to charge a higher fee. Thus, $-\alpha$ will be biased upwards. The first-stage of our instrumental variables is quite strong. We report the corresponding Cragg-Donald F Statistic at the bottom of Table 2 (Cragg and Donald (1993)). The corresponding F-statistics are in excess of 1,000 which is substantially greater than the typical rule of thumb (10) and the critical values for a weak instrument set reported in Stock and Yogo (2005).[17]

In the bottom panel of Table 2, we interpret the estimated coefficients in terms of elasticities. In our demand framework, the investor's elasticity of demand in a given market is given by $\alpha(1 - s_{iklt})f_{iklt}$.[18] Consistently across our main specifications, we find evidence suggesting that demand for brokerage services is relatively inelastic, with an elasticity of roughly 0.47. The estimates imply that if a broker increases the fee it charges by 1%, its market share will decrease by an associated 0.47%. This suggest that investor-broker relationships are relatively sticky in the sense that demand is relatively insensitive to trading fees.

V.B Value of Research

Most "high-touch" brokers try to attract clients' order flow by providing other types of services other than execution. One of the most visible services offered by brokers is access to research analysts. In addition to providing recommendations based on the valuation of firms' fundamentals, offering these services also ultimately translates into potentially profitable trading tips (Womack (1996); Barber, Lehavy, McNichols, and Trueman (2001); Barber, Lehavy, McNichols, and Trueman (2003); Jegadeesh, Kim, Krische, and Lee (2004); and Birru, Gokkaya, Liu, and Stulz (2019)).

Our framework allows us to test whether investors value sell-side research and whether sell-side research impacts order flow. In our demand specifications, our main research-related explanatory variables include the number of research analysts and the number of top-rated analysts as ranked by Institutional Investor. The average brokerage firm in our sample employs roughly 1.5 research analysts and 0.20 top research analysts in a given sector.

We report the coefficient point estimates corresponding to the number of research analysts and top research analysts in the top panel of Table 2 and interpret the corresponding magnitudes in the bottom panel of Table 2. The results in column (2) indicate that the average investor is willing to pay an additional 5.35bps (=1.72bps+3.63bps) per trade in order to have access to a top equity

[17]Stock and Yogo (2005) provide the critical values a weak instrument test for the maximal size (10%) of a 5% Wald test of $\beta = \beta_0$. The corresponding critical value with two endogenous regressors and two instruments is 7.03.

[18]The elasticity of demand is given by $\frac{\partial s_{iklt}}{\partial f_{iklt}} \times \frac{f_{iklt}}{s_{iklt}}$. Given the empirical framework, it is straightforward to show that $\frac{\partial s_{iklt}}{\partial f_{iklt}} = \alpha s_{iklt}(1 - s_{iklt})$ following eq. (5).

research analyst, while having access to additional a non-top analyst is worth 1.72bps. To put these numbers in perspective, the mean and standard deviation of brokerage fees is 13bps. Thus, the results in column (2) indicate that investors are indifferent between a one standard deviation decrease in fees and having access to an additional 2.5 top analysts (=13/5.35).

One potential concern is that the number of analysts and top analysts could be proxying for some other brokerage firm characteristic. While this is indeed possible, we believe it is unlikely that are our results are completely driven by unobservable characteristics for two reasons. First, we include broker-by-month fixed effects in our most stringent specifications, so it would have to be the case that research analyst coverage is proxying for some other brokerage firm characteristic at the broker-by-sector level over time. Second, in the proceeding section (Section VI) we show that investors have heterogeneous preferences over research. Our estimates indicate that those investors that we would expect to place no value on sell-side research, such as index fund managers and hedge funds, indeed place no value on sell-side research. Thus, if our results are driven by some unobserved broker-by-sector-by-investor characteristic, it would have to be that index fund investors and hedge fund also place little value on thatcharacteristic.

Overall, our estimates suggest that sell-side research, especially top-ranked research, helps drive institutional investor trading decisions and that investors appear to value sell-side research.

V.C 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 enrich our analysis by investigating how investors value order flow information.

First, we measure order flow information using the broker's centrality in the network of relationships between investment managers and brokers. In theory, we would expect more central brokers to trade with better performing investors who are themselves more likely to submit informed trades. Second, we identify instances in which the broker has received an informed order for 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 investors.

We present the point estimates in the top half of Table 2 and interpret the corresponding magnitudes in the bottom panel of Table 2. In each specification, we find that investors are more likely to trade with central brokers. The results in column (2) indicate that investors are willing to pay an additional 2.83bps per trade in order to trade with a broker who has a one standard-deviation higher centrality measure. The results are even more economically significant when we consider the informed broker measure. We find that the investors are willing to pay an additional 2-6bps in order to trade with an informed broker, which is similar to and actually slightly higher than the value investors place on sell-side research. Intuitively, the color that brokers provide about current order flow is potentially as important/valuable, if not more important, than the sell-side research analyst reports that are publicly released.

V.D Price Impact

Given the time and resources devoted by investors in making sure that trading is optimized, quality of execution is likely to be a key consideration for investors. Importantly, Anand, Irvine, Puckett, and Venkataraman (2012) show that institutional trading desks display persistent skill. Part of this skill may result from the choice of the most efficient brokers. Since brokers will have access to different networks of clients and different infrastructures to match opposite-sign orders from their clients, execution will likely be heterogeneous across brokerage firms. Furthermore, there might be specialization across brokers such that some brokers are more adept at trading some stocks than others.

We investigate how investors factor in execution quality when deciding where to route their orders. Table 2 presents the corresponding estimates. In columns (2)-(4) we instrument for expected price impact using lagged price impact, as described in Section IV to account for measurement error and potential endogeneity issues. In each specification, we estimate a negative and statistically significant relationship between a broker's trading price impact and the broker's market share. We interpret the magnitudes in the bottom panel of Table 2. The results in column (2) indicate that investors are willing to pay an additional 7bps in order to trade with a broker whose expected price impact is one standard-deviation (0.67%) lower. To the extent that expected price impact directly translates into higher execution costs, one might expect investors to trade-off price impact and brokers fees one-for-one. There are several potential explanations for our findings. First, our measure of price impact likely suffers from measurement error which could attenuate the estimated effect. Second, some investors could benefit from the price impact to the extent that the overall market is moving in their direction and/or has momentum. In terms of the variation in price impact, our estimates indicate that a one standard deviation increase in price impact corresponds roughly to half a standard deviation increase in brokerage fees (0.13%). Thus, in terms of the variation of the data, expected price impact has first-order impact on order flows.

V.E Trader Characteristics

A unique feature of our data set is that we also observe characteristics of the individual equity traders working for the brokerage firms in our Ancerno data. We are able to match the investor trading data from Ancerno with the trader-level data for about half of our sample. We re-estimate our baseline demand specification where we control for the characteristics of each broker's traders. Specifically, we control for the number of traders a firm employs, the average experience of those traders, and whether or not those traders engage in financial misconduct.

Table 3 presents the corresponding estimates. In each specification, we estimate a negative and statistically significant relationship between trader misconduct and a broker's market share. The results in column (1) indicate that investors are indifferent between a 1pp increase in misconduct and a 0.45bp increase in fees. Financial misconduct includes customer disputes, regulatory, and criminal offenses. These results suggest that financial misconduct costs brokerage firms money in the form of lower trading volumes. We also find that investors prefer to trade with firms that employ more experienced traders. The results in column (2) indicate that, on average, investors are willing to pay an additional 0.58bp to trade with a firm whose traders have an additional year of experience. However, we find evidence of a non-linear relationship. Investors prefer to trade with more experienced traders up until the trader has accumulated 14 years of experience. Beyond 14 years, investors actually prefer to trade with less-experienced traders. This suggests that traders may learn on the job over the first decade of their career, but their skills diminish over time. While investors appear to value the experience of the traders, we find little evidence suggesting that investors have strong preferences over the size of trading desks.

Using our trader-level data set, we can also determine the distance between investors and a brokerage firm's traders for roughly 30% of the trades in our sample. We re-estimate our demand specification controlling for distance and present the corresponding estimates in Table 4. The results indicate that investors prefer to trade with brokers who are located in the same city as the investor (within 100 miles). The economic magnitude of the estimated effect is substantial. The estimates in column (2) indicate that investors are willing to pay 10bp more per trade in order to trade with a broker who is located in the same city as the investor. The effect of being in the same city translates to a roughly one standard deviation decrease in brokerage fees. The effect is also somewhat surprising given that equity trades occur over the phone or electronically and not in person. These results also suggest that investors strongly prefer to trade with parties that they potentially know on a more intimate level and that relationships remain important in the industry. This is consistent with the idea that "trading is—and always has been—a relationship business."[19] Finally, we note that location in close proximity is not capturing investor or broker location in big cities (e.g. NYC) because our specifications include broker and investor fixed effects.

VI Investor Heterogeneity

In our baseline empirical analysis we implicitly assumed that investors have the same preferences across the broker characteristics. However, in practice, different investors may have different preferences. For example, an S&P 500 index fund may be extremely price sensitive relative to a hedge fund or active mutual fund. Similarly, an S&P Index fund would likely place no value on sell-side research while other investors may place a premium on high quality research. An advantage of our rich empirical stetting is that we are able to estimate demand at the investor-level.

VI.A Estimation

We re-estimate our baseline specification (eq. 7) where we allow an investor's preferences over fees (α_i) and other broker characteristics (β_i) to vary across investors. Recall from our earlier framework,

[19] The quote is from Johnson, Vice President of Market Structure and Technology at Greenwich Associates. [https://www.bloomberg.com/professional/blog/human-high-touch-trading-stay/] accessed 5/9/2019.

that an investor's indirect utility function from trading is:

$$u_{ijklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \xi_{iklt} + \epsilon_{ijklt}$$

In our baseline specification we assume that preferences are constant across investors such that:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

Here we consider two additional demand systems that are more flexible where we allow preferences to vary across investors.

First, we allow preferences to vary with investor characteristics D_i such that

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i$$

Where $D_i = [d_1, d_2, ...d_d]$ is a $d \times 1$ vector of investor characteristics including whether the investor is a hedge fund, index fund, high churn/volume fund (above average number of trades), high performing fund (above average returns), or a large fund (above average size).[20],[21] The matrix Π is a $(K+1) \times d$ matrix of coefficients that measure how investor preferences vary with investor characteristics. We estimate the specification where we interact the brokerage characteristics with our set of investor characteristics.

$$\ln s_{iklt} = -\sum_{i=1}^{d} \alpha_j f_{iklt} \times d_i + \sum x_{klt}\beta_j \times d_i + \mu_{lt} + \mu_{ikt} + \xi_{iklt} \tag{8}$$

As with our baseline specification, observations are at the investor-by-sector-by-month-by-broker level such that the market is defined in terms of all of the trades investor i executes in a given month t and sector k. The advantage of this approach is that we are able to let preferences vary across investor types and it allows us to easily interpret the estimated coefficients.

Second, we estimate a specification where we freely allow the preference coefficients to vary across investors

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \eta_i$$

where η_i is a $(K+1)$ vector that reflects investor-specific differences in preferences, conditional on the investor characteristics D_i. To implement this specification we estimate the following regression

[20] To identify index funds, we manually search the fund names in Ancerno for the word 'index' and flag the results with an indicator variable. Then, we aggregate this variable at the investment company-level by taking the average. Similarly, we identify hedge fund management companies in Ancerno using the procedure in Cotelioglu, Franzoni, and Plazzi (2019). With the understanding that the identification is made at the management company-level, we label these firms "hedge funds" for short.

[21] We compute investors' six-month trading performance at the end of month t as the value-weighted return of all the trades executed over the prior six-month period evaluated at the end of the month in question. In particular, the percentage performance of all trades started by a manager over the prior six months is computed using closing prices at the end of month t, with sell trades' performance computed as the negative of a buy trade performance. We value-weight the performance of all the trades in the same six-month horizon ending in month t.

at the investor-level:

$$\ln s_{iklt} = -\alpha_i c_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \mu_{ikt} + \xi_{iklt} \tag{9}$$

This allows us to recover the distribution of coefficients $\binom{\alpha_i}{\beta_i}$ without placing any parametric restrictions on the distribution of coefficients. Again, observations are at the investor-by-sector-by-month-by-broker level.

To recover the distribution of investor coefficients, we separately estimate eq. (9) at the investor-level such that we can recover each investor's preferences α_i and β_i. In other words, we are able to estimate our random-coefficients demand model using simple linear regression at the investor-level. This is in sharp contrast to the way one typically has to estimate a Berry, Levinsohn, and Pakes (1995) (BLP) type demand system. In the standard Berry, Levinsohn, and Pakes (1995) set-up, the econometrician only observes aggregate demand data, rather than individual demand data. Consequently, with aggregate data, one typically has to make parametric assumptions over the distribution of preferences (α_i, β_i), and estimates the model via GMM. Estimating the model via GMM with aggregate data involves solving a non-trivial contraction mapping for each set of parameters the econometrician searches over (Berry, Levinsohn, and Pakes (1995); Nevo (2000)). Because of our unique, detailed, micro data, where we observe each individual investor making thousands of decisions, we can estimate our demand model using simple regression at the investor-level. Furthermore, we do not need to make any parametric assumptions over the distribution of investor preferences (α_i, β_i). In most data sets, the researcher does not have enough observations at the individual-level to estimate individual-specific demand functions. For power considerations, we estimate eq. (9) at the investor-level where we restrict our sample to those 247 investors that have at least 1,000 observations.

We present the estimates corresponding to our additional demand specifications in Tables 5-7. Table 5 presents the results corresponding to eq. (8) where we interact broker and investor characteristics. We interpret the corresponding estimates across investor types in Table 6. Lastly, Table 7 displays the estimation results where we allow preferences to freely vary across investors (eq. 9). For ease of exposition, we discuss the results in Tables 5-7 in parallel in the proceeding subsections.

VI.B Fee Elasticity

We first examine how the elasticity of demand varies across institutional investors. Table 5a displays our estimates of how investors respond to fees. In panel (a) we report the estimates of α and how α varies across investor types. For example, the estimates in column (4) indicate that index fund managers are roughly 50% more sensitive to brokerage fees as other large investors. For convenience, we interpret the coefficients in terms of elasticities in Table 6a. The results suggest that elasticity of demand is most elastic among index funds (0.67) and the least elastic among hedge funds (0.38). This is intuitive given that one of the primary objective functions of index funds is to minimize costs and tracking error. Thus, it is not surprising that demand would be the most elastic among index funds. Conversely, it is not necessarily surprising that hedge funds have the most inelastic demand. Prime brokers for hedge funds provide a large variety of services, ranging from execution to leverage and share lending. This suggests thathedge funds-broker relationships are sticky and that hedge funds prioritize many other non-price/fee factors when making execution decisions.

We also allow the elasticity of demand to vary freely across investors in eq. (9). Table 9 reports the corresponding estimates, and Figure 3a displays the distribution of demand elasticities across investors. The average demand elasticity in the sample is 0.54 and the standard deviation is 0.56. The figure illustrates that demand among some investors, such as hedge fund investors, is relatively inelastic, where demand among other institutional investors, such as some index funds, has an elasticity greater than one.

VI.C Value of Research

Demand for sell-side research likely varies across investors. Some investors, such as mutual funds, may rely heavily on sell-side research while other investors such hedge funds may produce their own research. Table 5b presents our point estimates of investor preferences for research and shows how the preferences vary across investor types. We interpret the coefficients in Table 6b. The estimates indicate that hedge fund investors and index funds place no value on research. This makes sense as the former typically produces its own research and the latter has no need for research. Conversely, the average large investor (above average size) is willing to pay 1.11bp to have access to an additional sell-side research analyst and 3.26bps (=1.11+2.15) to have access to an additional top research analyst.

Again, we also allow preferences for research to vary freely across investors in eq. 9, and Table 7 and Figures 3b -3c report the corresponding estimates. While the average investor values research, Figure 3c indicates that many (10%+) investors place no value on top analysts.

VI.D Value of Information

Just as investors have different preferences over sell-side research, they may also have different preferences over the other sources of information produced by brokerage firms. Here, we examine how preferences over broker centrality and information vary across investors. Table 5c displays our point estimates of investor preferences over broker eigenvector centrality and whether the broker is informed where we allow the preferences to vary by investor type. We interpret the coefficients in panel (c) of Table 6. Our previous results indicate that investors, on average, value brokers that are more central in the trading network. Our results suggest that investors place drastically different values on broker centrality. While large funds are willing to pay an additional 0.74bps per trade to trade with an investor who is one standard deviation more central, hedge funds actually prefer to trade with less central brokers. The results in column (1) of panel (c) of Table 6 suggest that hedge funds are willing to pay an additional 2.85bps per trade to trade with an investor who is one standard deviation less central. One potential explanation for this finding is that hedge funds may be more concerned about concealing order flow and about brokers leaking a hedge fund's trades (Barbon, Di Maggio, Franzoni, and Landier (2018); and Di Maggio, Franzoni, Kermani, and Sommavilla (2018)). Thus, a hedge fund may prefer to trade with more peripheral brokers.

While index funds place a large premium on trading with a central brokers and hedge funds do not, the results flip when we look at which investors value trading with informed brokers. The results in column (2) of panel (c) of Table 6 indicate that hedge funds are willing to pay an additional 2.76bps per trade in order to trade with an informed broker. Conversely, index funds place no value on trading with an informed broker. This makes sense as index funds have no use for this information, while hedge funds potentially benefit dramatically by being privy to informed order flow.

We allow preferences for centrality and information to vary freely across investors in eq. (9), and Table 7 and Figures 3d and 3e report the corresponding estimates. The results echo our previous findings, indicating that while most investors prefer to trade with central and informed brokers, the intrinsic value of these characteristics differs dramatically across investors.

VI.E Price Impact

We also examine how different investors factor in the expected price impact of trading when making execution decisions. Table 5d presents our point estimates of investor preferences over expected price impact and we interpret the coefficients in Table 6d. Consistent with our earlier findings, we find that the average investor is willing to pay an additional 2bp in order to have a standard deviation decrease in expected price impact. Index investors appear toplace the highest value on trading execution. While most investors prefer to trade with brokers with a low expected price impact, we find some evidence that hedge funds are actually more likely to trade with brokers who generate a higher price impact. This could be because price impact rises with the informational content of trades and hedge funds are the most likely investors to place informed trades. Hence, the brokers that are chosen by hedge funds are more likely to have higher price impact.

Table 7 and Figure 3f present the estimates where we allow an investor's sensitivity to expected price impact to vary freely across investors (eq. 9). The estimates are in line with our previous results, but theestimated average effect is slightly larger. The average investor is willing to pay an additional 3.50bps to trade with a broker with a 1 standard deviation lower expected price impact.

VII Soft-dollars and Management Fees

Brokers traditionally provide bundled services to investors, bundling execution, research and other brokerage services. Over the past 20 years, there has been a push among investors and in policy circles to unbundle brokerage services to improve market competitiveness and transparency. Most recently, as part of MiFID II, European regulators are forcing brokers to unbundle their services. Bundling allows institutional investors to pay for research and other brokerage services with soft-dollars through execution fees rather than directly paying for these services with hard-dollars. These type of transaction fees are not reported in the fund's expense ratio but are subtracted from the fund's returns.[22] The potential concern with soft-dollars payments is that they are borne by the end-investor and not disclosed by the fund. Hence, paying for research with soft-dollars results in investment managers under-reporting fund management fees.

The term soft-dollar payments does not necessarily have a uniform definition in the industry and broadly incorporates two different types of research-related transactions (Blume (1993)). The first, and most common type of transaction, is when an investor uses broker commissions to pay a broker for research and other services that the broker produced in-house. In the second type of transaction, the investor uses broker commissions to pay for research and other services obtained from a third party. The broker then pays a portion of the corresponding commissions to the relevant third party. We use our framework to focus on soft-dollar payments for in-house research. We focus on these types of soft-dollar payments because they are more common (Blume (1993)) and can be more directly measured using our estimates.

Our framework from Section II and the heterogeneous coefficient estimates from Section VI (eq. 9) allow us to quantify soft-dollar in-house research related payments in the brokerage industry. Our empirical estimates measure how each investor precisely values the in-house research produced by brokers, and how much more an investor is willing to pay on a per-transaction basis to have access to research. We then use these estimates to calculate how much larger fund reported management fees would be if they included the value of soft-dollar in-house research related payments in their fees.

VII.A Quantifying the Soft-Dollars

We use our empirical estimates to quantify the total value investors obtain from having access to sell-side research. To calculate the total value of sell-side research we compute the compensating variation required if we were to remove sell-side research from the market place. The compensating variation tells us how much investors would be willing to pay in hard-dollars to have access to sell-side research. We can then use the estimate of compensating variation to determine how much higher reported management fees would be if investors paid for research with hard-dollars.

Its important to note that the compensating variation calculation is inherently a partial equilibrium calculation where the characteristics of brokers are held fixed. If regulators were to force investors to pay for research with hard-, rather than soft-, dollars, the quantity of hard-dollars in equilibrium would depend on competition among brokers and bargaining between investors and brokers, neither of which we have explicitly modeled. The advantage of focusing on compensating variation is that it can be directly calculated from our investor demand estimates without having to take a stance on the supply-side of the model or the nature of competition.

We calculate the compensating variation at the investor by market-level using our demand estimates. We calculate the compensating variation of investor i in sector k at time t as the expected profits of trading when the investor has access to sell-side research ($(E]\pi_{ikt}]$) relative to the expected

[22] http://www.finra.org/investors/funds-and-fees

profits of trading when the investor does not have access to sell-side research $(E]\pi_{ikt}^{No\,Research}])$:

$$CV_{ikt}^{Research} = E[\pi_{ikt}] - E[\pi_{ikt}^{No\,Research}]$$

Following Petrin (2002), compensating variation in our discrete choice framework is given by

$$CV_{ikt}^{Research} = \frac{\ln\left(\sum_{l\in\mathcal{L}_{ikt}} exp(\overline{u}_{iklt})\right)}{\alpha_i} - \frac{\ln\left(\sum_{l\in\mathcal{L}_{ikt}} exp(\overline{u}_{iklt}^{No\,Research})\right)}{\alpha_i} \tag{10}$$

where $\overline{u}_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt}$ is the average utility derived by investor i from trading in sector k with broker l at time t and $\overline{u}_{iklt}^{No\,Research} = \overline{u}_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt} - X_{klt}^{Research}\beta_i^{Research}$ is the average utility derived by investor i from trading in sector k with broker l at time t excluding the utility from research $(X_{jkt}^{Research}\beta_i^{Research})$. Intuitively, the compensating variation is an increasing function of the utility of research $(X_{jkt}^{Research}\beta_i^{Research})$ aggregated across all brokers available to an investor in a given sector, $\mathcal{L}_{ikt}$. All else equal, the more utility an investor derives from research, the greater the required compensating variation. The scaling term $\frac{1}{\alpha_i}$ converts the required compensating utility in terms of profits/fees. Using our demand estimates (eq. 9) we calculate compensating variation at the investor-by-market level.[23]

VII.B Results

Figure 4 plots the distribution of compensating variation at the investor-by-market-level. For purposes of making an apples-to-apples comparison, we report the compensating variation for those markets where we observe at least one active research analyst. The average compensating variation is 3bps, which implies that the investor would be willing to pay an additional 3bp per trade in order to have access to sell-side research. Again, the value of research varies dramatically across the population of investors, with 25% of investors placing essentially no value (less than 0.5bps) on sell-side research. At the other extreme, 10% of investors would be willing to pay more than 7bps per trade to have access to outside research (Figure 4, Table 8) .

We can use the compensating variation estimates to provide an estimate of how much higher reported management fees would be if investors had to pay for research with hard-dollars. Compensating variation tells us the investors' perceived value of the research they consume through soft-dollar payments on a per-trade basis or, in other words, how much investors would be willing to pay in hard-dollars for the research they consume on a per-trade basis. Because our estimates of the value of research are on a per-trade basis, we annualize these implied research costs by multiplying

[23] Notice that in our demand specification we can write an investors indirect utility as $\overline{u}_{iklt} = \ln(s_{iklt}) + \phi_{ikt}$, where ϕ_{ikt} is some market (investor-sector-time) specific constant. Thus we can compute the compensating variation empirically at the investor by market-level as

$$CV_{ikt}^{Research} = \left(\frac{\ln\left(\sum_{l\in\mathcal{L}_{ikt}} s_{ijkt}\right) - \ln\left(\sum_{l\in\mathcal{L}_{ikt}} s_{iklt} exp(-X_{klt}^{Research}\beta_i^{Research}\right)}{\alpha_i}\right)$$

where $X_{klt}^{Research}\beta_i^{Research}$ is the utility investor i derives from research.

them by what fraction of an investor's portfolio is traded in a given year (the investor's portfolio turnover times two).[24],[25] Lastly, we compare the annualized implied research costs relative to the fund's annual management fees to determine how much firms under-report management fees relative to the value they extract from soft-dollar research payments:

$$\frac{Annual\,Soft\,Dollars_{lt}}{Management\,Fees_{lt}} = \frac{\bar{CV}_{it}^{Research} \times Portfolio\,Turnover_{it} \times 2}{Management\,Fees_{t}}. \tag{11}$$

Figure 5 and Table 8 display our estimates of how much management fees are potentially under-reported due to soft-dollar related research payments. Specifically, Figure 5 reflects the annual value of research obtained through soft-dollar payments relative to management fees at the investor-by-year level. The estimates indicate that the average investor in our sample under-reports management fees by 4.30%. Again, there is substantial heterogeneity across investors. While management fees are not under-reported for 25% of our sample ($Underreporting < 0.25\%$), they are under-reported by more than 20% at some firms. The top quartile of funds in terms of under-reporting under-report management fees by roughly 15% on average. Our results suggest that for many firms in our sample, the value of soft-dollar research related payments is substantial.

VIII Conclusion

Institutional investors continue to rely on high-touch brokerage transactions in equity markets even with the growth of alternative trading platforms. Given the sophistication of institutional investors and how well-developed equity markets are, why do institutional investors trade through brokers? This paper is a first step towards a better understanding and quantifying the value thatbrokers create.

Our results indicate that brokers create value for investors by providing efficient execution, sell-side research, and order flow information. While the average investor values these broker services, there is substantial heterogeneity across investors. Hedge funds place almost no value on sell-side research, but place a large premium on order flow information. Conversely, large institutional investors are willing to pay up to 5-10bp more per trade in order to have access to sell-side research analysts.

Investors traditionally have paid for these research services with bundled-fee commissions, or soft-dollars, which potentially allows them to under-report their management fees. Our estimates

[24] We calculate fund turnover and management fees for mutual funds as reported by CRSP Mutual Fund data. Because the Ancerno data is at the management company-level, but the mutual fund data is at the fund-level, management companies in Ancerno (which we label investor) are matched to multiple mutual funds. We calculate the average turnover rate and manager expenses at the investor-by-year level where we take the equal weighted average across all of an investor's corresponding mutual funds. We calculate management fees for hedge funds as reported by TASS. We calculate portfolio turnover for hedge funds based on the average trading volume in our Ancerno sample.

[25] Fund turnover is calculated as the value of all transactions (buying, selling) divided by two, then divided by a fund's total holdings. Because we are interested in the number of trades an investor makes in a given year, we multiply the investor's portfolio turnover by two to account for both sell (stocks removed from the portfolio) and buy trades (stocks added to the portfolio).

suggest that while the amount of under-reporting is small for the average institutional investor, management fees are under-reported by up to 10-20% at some firms as a result of soft-dollar research payments. Overall, our results help explain why high-touch broker trading remains prominent in institutional equity markets.

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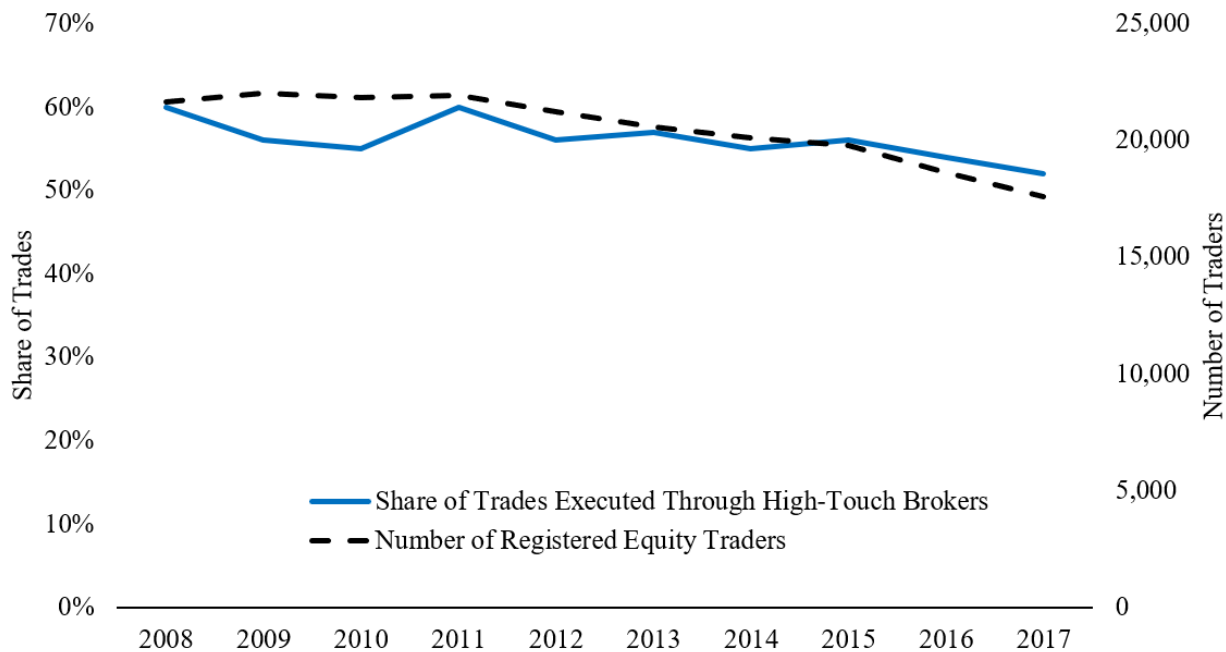
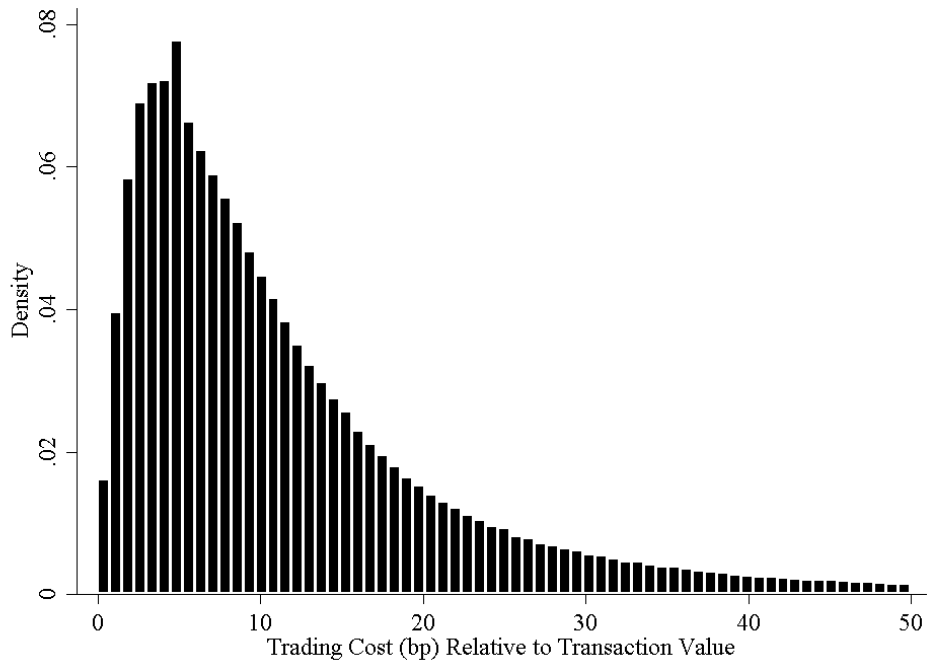
Figure 1: Share of High-Touch Broker Trades and the Number of Equity Traders in the U.S.



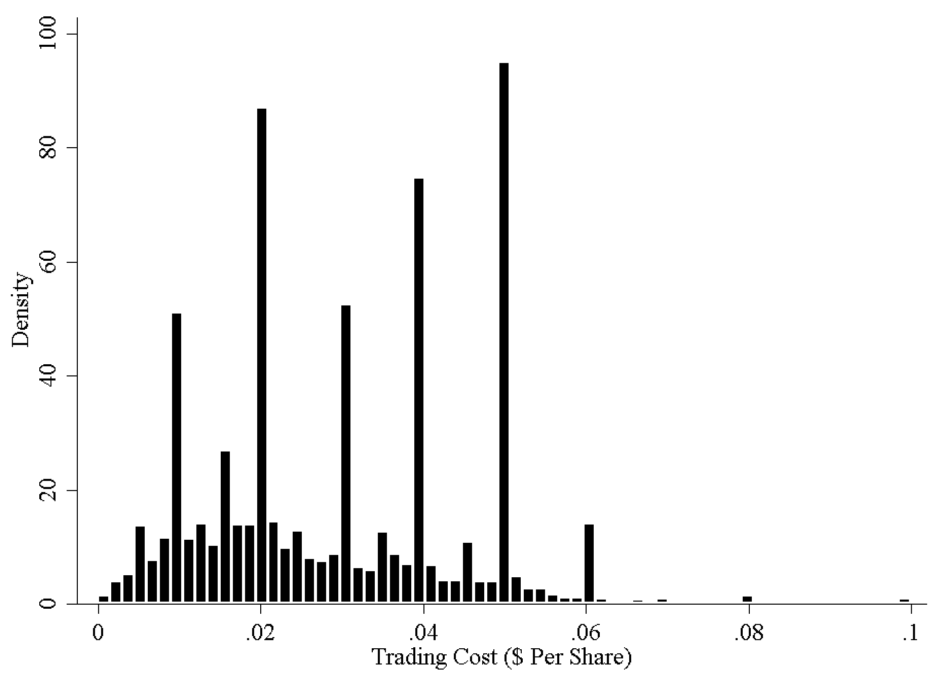
Note: The blue line displays the share of single-stock trades executed with high-touch broker sales traders. Data on trade execution comes from survey data conducted and reported by Greenwich Associates in the Greenwich Associates US Equity Investors Survey (2015-2017). The black line displays the number of equity traders registered in the U.S. by year. We calculate the number of equity traders as the number of individuals who are licensed with the Financial Industry Regulatory Authority as equity traders (i.e. the number of individuals who hold a Series 55 "Equity Trader Examination" license).

Figure 2: Brokerage Fees

(a) Fees (% of Transaction Value)



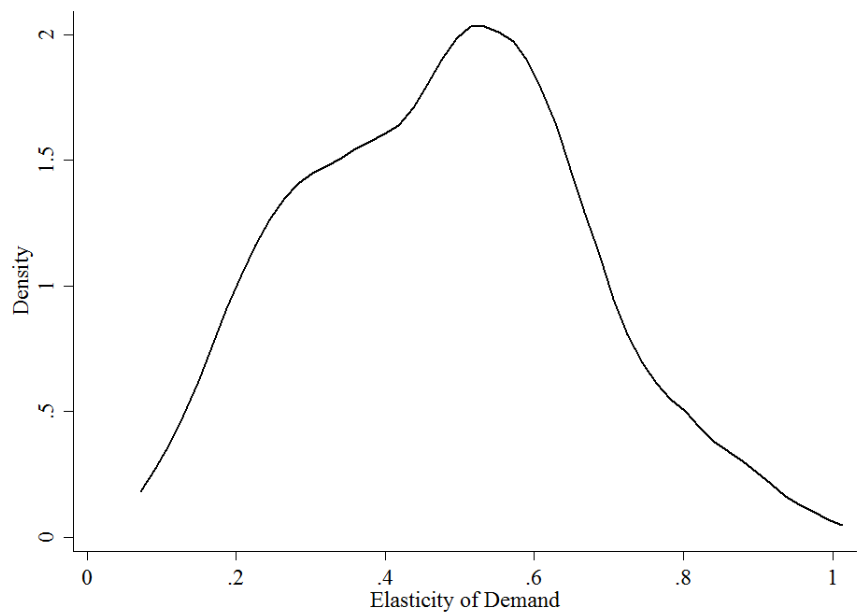
(b) Fees ($ per Share)



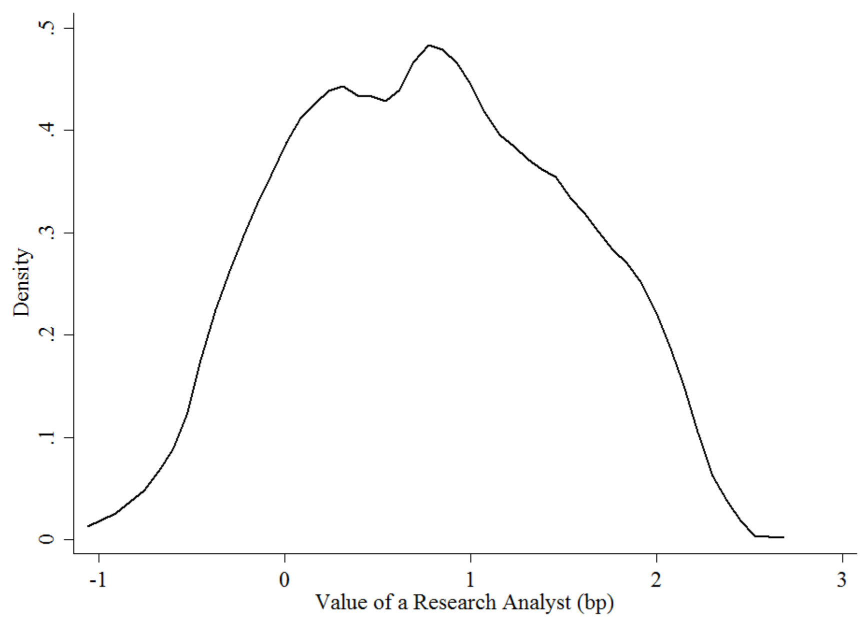
Note: Figures 2 displays the distribution of fees charged by brokerage firms in terms of the cost relative to the value of the transaction and the cost in terms of dollars per share. Observations are at the trade level.

Figure 3: Preference Heterogeneity

(a) Elasticity of Demand



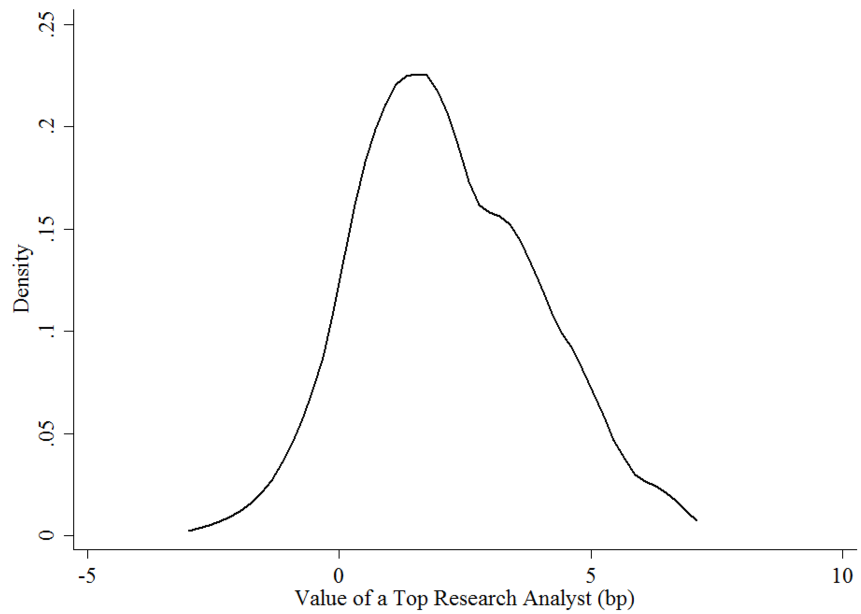
(b) Value of an Additional Research Analyst (bp)



Note: Figure 3 panels (a)-(f) display the estimated distributions of demand elasticities, value placed on additional Research Analyst, value placed on an additional Top Research Analyst, value of a 1 standard deviation increase in broker Eigenvector Centrality, the value of trading with an "informed" broker, and the value of a 1pp decrease in Price Impact. Observations are at the investor level, and are weighted by investor trading activity. The distributions correspond to the estimates reported in Table 7. We compute the average elasticity of demand for each investor type as the average of $-\alpha * (1 - s) * fee$. We compute the value of research, information, and price impact for each investor type as the average of the ratio of the coefficient of interest divided by an investor's sensitivity with respect to fees ($-\alpha$).

Figure 3: Preference Heterogeneity (Continued)

(c) Value of an Additional Top Research Analyst (bp)



(d) Value of 1 SD Inc. in Broker Centrality (bp)

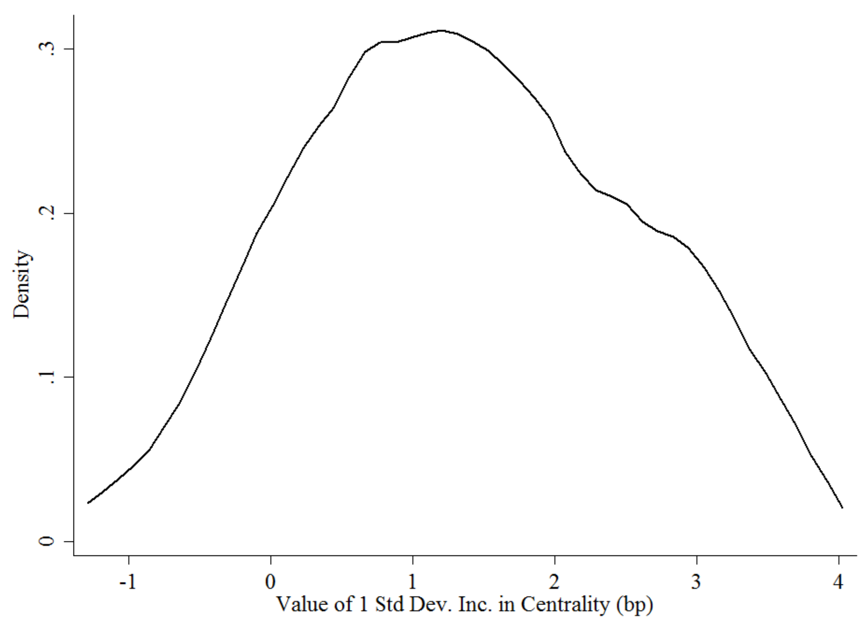
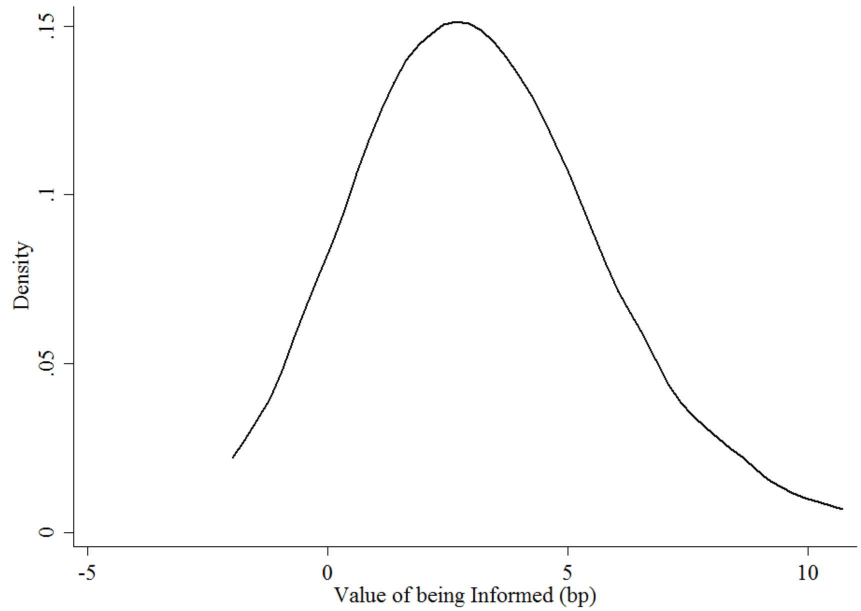


Figure 3: Preference Heterogeneity (Continued)

(e) Value of Information (bp)



(f) Price Impact

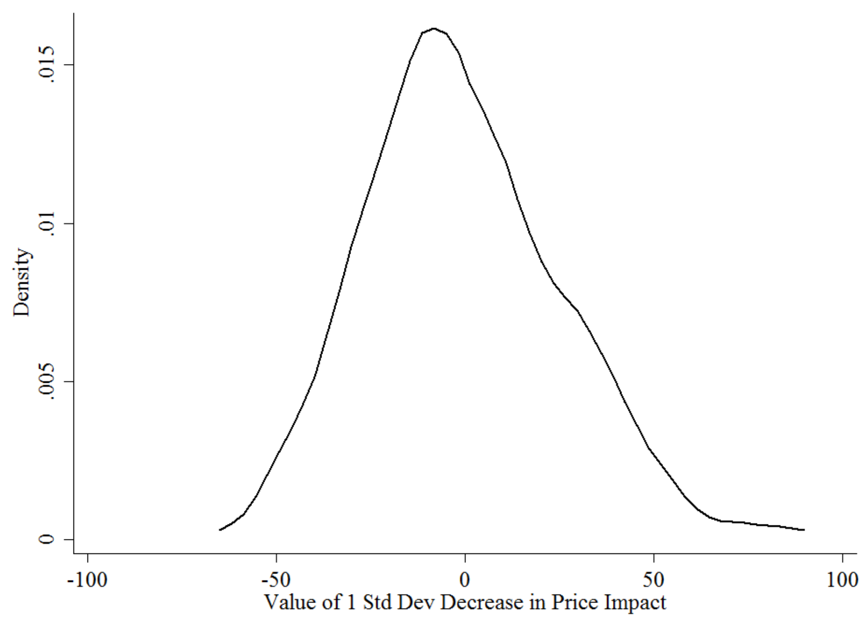
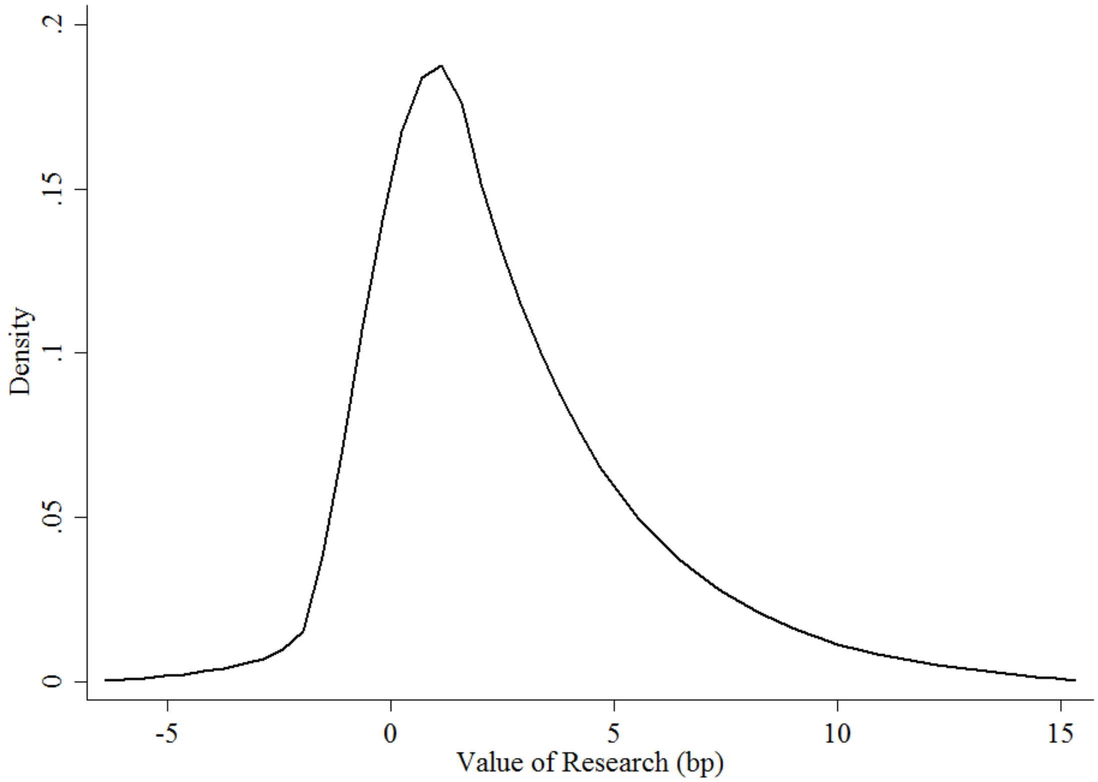
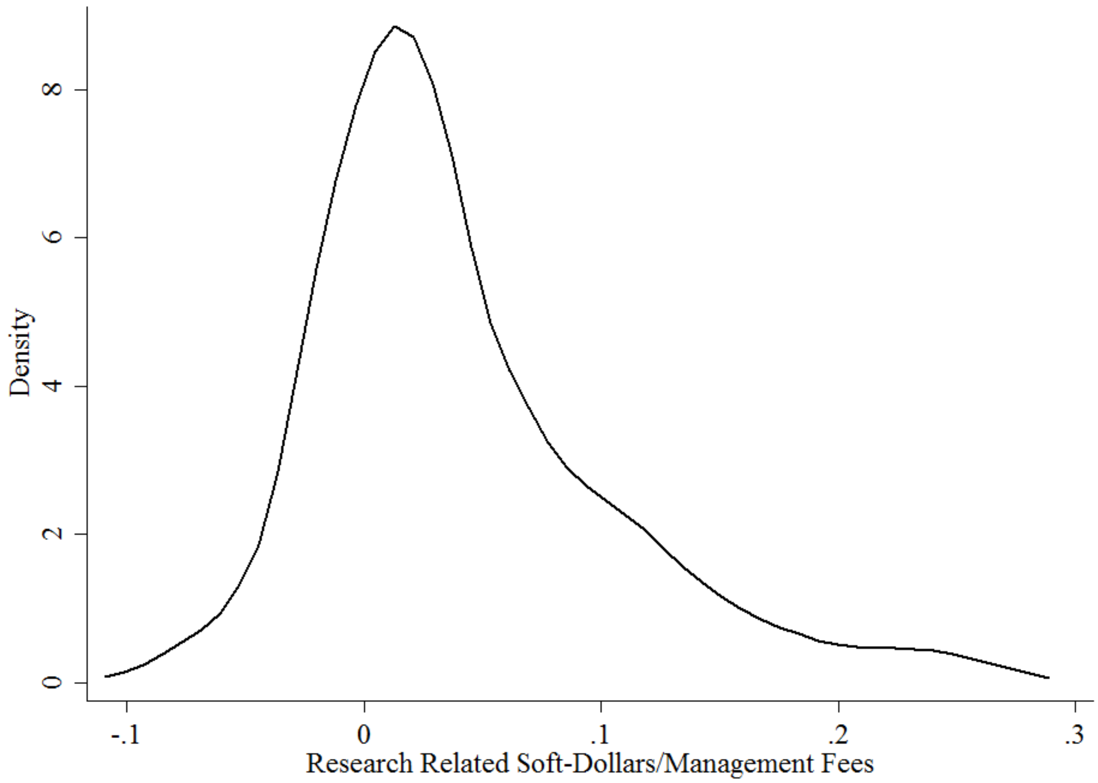


Figure 4: Total Value of Research



Note: The figure presents the distribution of compensating variation if we were to remove sell-side research from the market. In other words, how much would we have to compensate each investor to make them indifferent between a world with and without sell-side research. We compute the compensating required for each investor at the market level according to eq. (10). Observations are at the investor-by-month-by-sector level and are weighted by investor trading activity.

Figure 5: Research Related Soft-Dollars Relative to Management Fees



Note: The figure presents the distribution of the annual value of soft-dollar research payments relative to the investor's management fees. Observations are at the investor-by-year level. We calculate the annual value of soft-dollar research payments based on the compensating variation required if we were remove sell-side research from the market (eq. 10; Table 4). Specifically, we calculate the annual value of soft-dollar research related payments as the average compensating variation at the investor-by-year level multiplied by how often the institutional investor turns over his/her portfolio. To account for outliers, we truncate the distribution at the 2.5% and 97.5% level.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Fees($ per share)	7,224,298	0.031	0.016
Fees (%)	7,224,298	0.13%	0.13%
Price Impact	7,224,298	0.19%	0.67%
Research Analysts:			
Number of Analysts	7,224,298	1.47	2.40
Number of Top Analysts	7,224,298	0.16	0.47
Broker Information:			
Eigenvector Centrality	6,580,372	0.052	0.10
Informed Broker (Di Maggio et al. 2018)	7,224,298	27%	44%
Equity Traders:			
Number of Traders	3,397,871	255	238
Pct of Traders Receiving Misconduct Disclosures	3,397,871	0.20%	0.61%
Average Trader Experience	3,377,309	11.65	2.66
Distance (miles)	2,048,359	668	806
Close Distance (Dist.<100 miles)	2,048,359	33%	47%
Institutional Investors:			
Hedge Fund	7,122,102	0.049	0.22
Index Fund	7,224,298	0.029	0.10
Number of Trading Partners (Per Market)	7,224,298	16.98	11.87

Note: Table 1 displays the summary statistics corresponding to our data set. Each variable is described in detail in Section IV.B. Observations are at the investor by month by sector by broker level.

Table 2: Broker Choice

	(1)	(2)	(3)	(4)
Fees (α)	-152***	-413***	-401***	-402***
	(4.32)	(7.83)	(7.01)	(6.94)
Price Impact:	3.31***	-42.6**	-22.6*	-26.0**
	(0.35)	(19.2)	(12.8)	(12.7)
Research:				
Number of Analysts	0.068***	0.071***	0.031***	0.035***
	(0.0037)	(0.0038)	(0.0024)	(0.0017)
Number of Top Rated Analysts	0.15***	0.15***	0.067***	0.065***
	(0.010)	(0.011)	(0.0060)	(0.0043)
Information:				
Eigenvector Centrality	1.30***	1.17***	0.52***	0.31***
	(0.064)	(0.066)	(0.040)	(0.045)
Informed Broker	0.31***	0.26***	0.12***	0.10***
	(0.015)	(0.014)	(0.0068)	(0.0042)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker Fixed Effects			X	
Broker×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X
Cragg Donald F-Statistic for IV		6,300	2,900	1,300
Observations	6,484,127	5,756,568	5,756,564	5,755,998
R-squared	0.304	0.269	0.298	0.315
Mean Elasticity with Respect to Fees	0.18	0.49	0.47	0.47
Value of Research:				
Value of an Additional Analyst (bp)	4.47	1.72	0.77	0.87
Value of an Additional Top Analyst (bp)	9.87	3.63	1.67	1.62
Value of Information:				
Value of 1σ Increase in Eigenvector Centrality (bp)	8.54	2.83	1.30	0.77
Value of an Informed Broker (bp)	20.39	6.30	2.99	2.49
Value of 1σ Decrease in Price Impact (bp)	-1.46	6.91	3.78	4.33

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 7). The unit of observation is at the investment 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 fees in percentage terms relative to the value of the transaction. As described in the text we instrument for fees using the average historical fee charged by the broker in terms of cents per share divided by the share price of the stock being traded. The logic behind the instrument that brokerage firms charge investment managers on per-share basis, which is relatively sticky, but what investment managers care about is the cost of the trade relative to the value of the transaction. We instrument for price impact using the lagged price impact to account for measurement error. 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. In the bottom half of the table we interpret the coefficient estimates. Elasticity of demand is calculate as the average of $-\alpha * (1-s) * fee$. We compute the value of each independent variable as the ratio of the coefficient of interest divided by an investor's sensitivity with respect to fees ($-\alpha$). For example we calculate the value of an analyst in column (1) as 10,000 $\times$ 0.068/152 = 4.47bps.

Table 3: Broker Choice and Trader Characteristics

	(1)	(2)	(3)	(4)
Fees	-481***	-482***	-482***	-482***
	(10.3)	(10.3)	(10.3)	(10.3)
Trader Characteristics:				
Misconduct	-2.18**			-1.83*
	(1.00)			(1.01)
Trader Experience		0.22***		0.21***
		(0.040)		(0.042)
Trader Experience^2		-0.0080***		-0.0077***
		(0.0015)		(0.0015)
Number of Traders (100s)			-0.0054	0.055
			(0.042)	(0.050)
Number of Traders$^2(100s)$			-0.0033	-0.0074*
			(0.0035)	(0.0041)
Sector×Investor×Time Fixed Effects	X	X	X	X
Other Controls	X	X	X	X
Broker Fixed Effects	X	X	X	X
IV (Commissons & Price Impact)	X	X	X	X
Cragg Donald F-Statistic for IV	1,100	1,000	1,100	1,000
Observations	3,134,050	3,120,165	3,134,050	3,120,165
R-squared	0.294	0.293	0.294	0.293
Mean Elasticity	0.57	0.57	0.57	0.57
Value of Trader Characteristics:				
1pp Inc. in Misc. (bp).	-0.45			-0.38
1 Year Inc. in Trader Experience (bp):		0.58		0.52
100 Inc. in Number of Traders			-0.45	0.37

Note: The table displays the estimation results corresponding to our discrete choice broker model where we allow (eq. 8). The unit of observation is at the investment 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. The independent variable Misconduct measures the share of equity traders working for the brokerage firm in a given year that receive misconduct disclosures, where misconduct is defined as per Egan, Matvos and Seru (2019). Trader Experience measures the average trader experience in years of a the equity traders working at a brokerage. Number of Traders measures the number of traders working at a brokerage firm and is measured in 100s of traders. We measure fees in percentage terms relative to the value of the transaction. As described in the text we instrument for fees using the average historical fees charged by the broker in terms of cents per share divided by the share price of the stock being traded. The logic behind the instrument that brokerage firms charge investment managers on per-share basis, which is relatively sticky, but what investment managers care about is the cost of the trade relative to the value of the transaction. Other controls include: Price Impact, Number of Research Analysts, Number of Top Research Analysts, Number of Buy Recommendations, Broker Eigenvector Centrality, and Informed. We instrument for price impact using the lagged price impact to account for measurement error. 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.

In the bottom half of the table we interpret the coefficient estimates. Elasticity of demand is calculate as the average of $-\alpha * (1-s) * fee$. We compute the value of each independent variable as the ratio of the coefficient of interest divided by an investor's sensitivity with respect to fees ($-\alpha$). For example we calculate the value of a 1pp increase in misconduct in column (1) as 10,000 × 2.18/481×-1.00% = -0.45bps. We calculate the marginal value of a year of Trader Experience at the average value of Trader Experience (1 years). Similarly, we calculate the marginal value of an additional 100 traders at the average value of Number of Traders. The average firm in our sample employs 250 equity traders.

Table 4: Broker Choice and Distance

	(1)	(2)	(3)	(4)
Fee	-147***	-404***	-400***	-397***
	(7.61)	(11.4)	(9.84)	(9.58)
Close Distance (Less than 100 miles)	0.41***	0.42***	0.34***	0.35***
	(0.047)	(0.051)	(0.052)	(0.054)
Sector×Investor×Time Fixed Effects	X	X	X	X
Other Controls	X	X	X	X
Broker Fixed Effects			X	
Broker ×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X
Cragg Donald F-Statistic for IV		1,500	780	310
Observations	1,943,740	1,835,253	1,835,252	1,834,932
R-squared	0.299	0.283	0.308	0.340
Mean Elasticity	0.18	0.47	0.47	0.47
Value Being Less than 100 miles (bp)	27.89	10.40	8.50	8.82

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 7). The unit of observation is at the investment 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. Close Distance is a dummy variable indicating that the broker and investor are located within 100 miles of each other. We measure fees in percentage terms relative to the value of the transaction. As described in the text we instrument for fees using the average historical fees charged by the broker in terms of cents per share divided by the share price of the stock being traded. The logic behind the instrument that brokerage firms charge investment managers on per-share basis, which is relatively sticky, but what investment managers care about is the cost of the trade relative to the value of the transaction. Other controls include: Price Impact, Number of Research Analysts, Number of Top Research Analysts, Number of Buy Recommendations, Broker Eigenvector Centrality, and Informed. We instrument for price impact using the lagged price impact to account for measurement error. 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.

In the bottom half of the table we interpret the coefficient estimates. Elasticity of demand is calculate as the average of $-\alpha * (1-s) * fee$. We compute the value of Distance as the ratio of the Distance coefficient divided by an investor's sensitivity with respect to fees $(-\alpha)$. For example, we calculate the value of being less than 100 miles apart in column (1) as 10,000 $\times$ 0.41/147$\times$ = 27.89bps.

Table 5: Broker Choice

(a) Broker Choice - Fee Sensitivity

	(1)	(2)	(3)	(4))
Fees	-132***	-291***	-275***	-281***
	(7.51)	(11.0)	(10.5)	(10.3)
× Hedge Fund	42.1***	132***	120***	122***
	(7.00)	(9.32)	(9.27)	(9.13)
× Index Fund	-23.4	-291***	-282***	-303***
	(31.4)	(43.4)	(42.8)	(43.3)
× Large Investor	9.26	-113***	-114***	-114***
	(6.44)	(8.43)	(8.32)	(8.21)
× High Performance	-3.79	22.2***	23.8***	26.0***
	(6.91)	(8.31)	(8.04)	(7.79)
× High Churn	-49.2***	-90.3***	-91.5***	-87.0***
	(6.92)	(8.20)	(7.86)	(7.77)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker Fixed Effects			X	
Broker ×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X

Table 5: Broker Choice (Continued)

(b) Broker Choice - Research

	(1)	(2)	(3)	(4)
Number of Analysts	0.012**	0.014**	-0.031***	-0.027***
	(0.0051)	(0.0054)	(0.0057)	(0.0054)
× Hedge Fund	-0.034***	-0.036***	-0.032***	-0.031***
	(0.0048)	(0.0050)	(0.0048)	(0.0048)
× Index Fund	-0.073***	-0.054***	-0.055**	-0.051**
	(0.022)	(0.021)	(0.021)	(0.022)
× Large Investor	0.060***	0.063***	0.063***	0.062***
	(0.0045)	(0.0049)	(0.0047)	(0.0047)
× High Performance	0.0074*	0.0073*	0.0083**	0.0090**
	(0.0041)	(0.0042)	(0.0040)	(0.0040)
× High Churn	0.019***	0.017***	0.022***	0.023***
	(0.0043)	(0.0044)	(0.0042)	(0.0042)
Number of top Rated Analysts	0.023	0.027	-0.054***	-0.062***
	(0.017)	(0.017)	(0.015)	(0.015)
× Hedge Fund	-0.12***	-0.12***	-0.12***	-0.12***
	(0.017)	(0.017)	(0.017)	(0.016)
× Index Fund	-0.054	-0.062	-0.052	-0.065
	(0.063)	(0.064)	(0.063)	(0.062)
× Large Investor	0.16***	0.15***	0.15***	0.15***
	(0.014)	(0.014)	(0.014)	(0.014)
× High Performance	-0.023	-0.021	-0.022	-0.019
	(0.015)	(0.015)	(0.015)	(0.015)
× High Churn	0.059***	0.051***	0.051***	0.056***
	(0.016)	(0.016)	(0.015)	(0.015)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker Fixed Effects			X	
Broker ×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X

Table 5: Broker Choice (Continued)

(c) Broker Choice - Information

	(1)	(2)	(3)	(4)
Eigenvector Centrality	0.48***	0.41***	-0.29***	-0.52***
	(0.083)	(0.088)	(0.10)	(0.11)
× Hedge Fund	-1.18***	-1.11***	-1.13***	-1.09***
	(0.10)	(0.11)	(0.10)	(0.10)
× Index Fund	0.40	0.56*	0.68**	0.86***
	(0.30)	(0.30)	(0.30)	(0.31)
× Large Investor	0.70***	0.63***	0.66***	0.65***
	(0.077)	(0.082)	(0.087)	(0.089)
× High Performance	0.33***	0.33***	0.33***	0.34***
	(0.068)	(0.071)	(0.070)	(0.072)
× High Churn	0.40***	0.36***	0.40***	0.41***
	(0.066)	(0.070)	(0.072)	(0.073)
Informed Broker	0.13***	0.12***	-0.066***	-0.093***
	(0.023)	(0.022)	(0.022)	(0.020)
× Hedge Fund	-0.031	0.0073	0.010	0.015
	(0.021)	(0.020)	(0.020)	(0.019)
× Index Fund	-0.16**	-0.087	-0.097	-0.088
	(0.069)	(0.076)	(0.075)	(0.073)
× Large Investor	0.21***	0.17***	0.21***	0.21***
	(0.021)	(0.021)	(0.021)	(0.021)
× High Performance	-0.018	-0.021	-0.013	-0.013
	(0.018)	(0.017)	(0.016)	(0.016)
× High Churn	0.036*	0.0073	0.035**	0.038**
	(0.019)	(0.019)	(0.018)	(0.018)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker Fixed Effects			X	
Broker ×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X

Table 5: Broker Choice (Continued)

(d) Broker Choice - Price Impact

	(1)	(2)	(3)	(4)
Price Impact	1.93***	-1.53	40.0*	34.8
	(0.53)	(23.4)	(23.4)	(26.5)
× Hedge Fund	0.20	75.7***	48.8**	44.2**
	(0.55)	(21.6)	(21.0)	(20.9)
× Index Fund	-19.9***	-151***	-224***	-246***
	(2.08)	(51.4)	(52.1)	(54.1)
× Large Investor	1.76***	-70.4***	-76.9***	-71.4***
	(0.47)	(20.6)	(21.4)	(22.5)
× High Performance	-0.20	-12.8	-14.6	-14.0
	(0.43)	(19.2)	(18.6)	(18.3)
× High Churn	1.20***	22.1	13.2	10.9
	(0.46)	(20.5)	(18.8)	(18.6)
Sector×Investor×Time Fixed Effects	X	X	X	X
Broker Fixed Effects			X	
Broker ×Time Fixed Effects				X
IV (Commissons & Price Impact)		X	X	X
Observations	6,483,725	5,756,217	5,756,213	5,755,645
R-squared	0.308	0.262	0.291	0.309

Panels (a)-(d) displays the estimation results corresponding to our discrete choice broker model where we allow preferences to vary across investor types (eq. 8). Each column corresponds to a single regression specification across each panel such that columns (1) of panels (a), (b), (c) and (d) all correspond to the same regression specification. The unit of observation is at the investment 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. Large Investor indicates that the portfolio size of the investor is above average. High performance indicates that the investor's returns in our sample are above average. High churn indicates that the investor's number of trades is above average in our sample. We measure fees in percentage terms relative to the value of the transaction. As described in the text we instrument for fees using the average historical fee charged by the broker in terms of cents per share divided by the share price of the stock being traded. The logic behind the instrument that brokerage firms charge investment managers on per-share basis, which is relatively sticky, but what investment managers care about is the cost of the trade relative to the value of the transaction. We instrument for price impact using the lagged price impact to account for measurement error. 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: Value of Broker Services: Research and Information

(a) Elasticity of Demand

	Elasticity of Demand
Hedge Fund	0.38
Index Fund	0.67
Large Investor	0.50
High Performance	0.45
High Churn	0.50
Average	0.47

(b) Value of Research (bp)

	Additional Analyst	Additional Top Analyst
Hedge Fund	0.02	-2.10
Index Fund	-0.05	0.53
Large Investor	1.11	2.15
High Performance	0.84	0.70
High Churn	1.01	1.91
Average	0.72	1.07

(c) Value of Information (bp)

	Broker Centrality (σ Inc.)	Informed Broker
Hedge Fund	-2.85	2.76
Index Fund	1.59	0.30
Large Investor	0.74	3.33
High Performance	0.53	2.05
High Churn	0.78	2.71
Average	0.19	2.13

(d) Value of Price Impact (bp)

	Price Impact (σ Decrease)
Hedge Fund	-7.33
Index Fund	17.79
Large Investor	4.75
High Performance	2.55
High Churn	2.37
Average	1.69

Panels (a)-(d) presents the elasticity of demand and value of research, information, and price impact corresponding to the results displayed in Table 5 (column 4). We compute the average elasticity of demand for each investor type as the average of $-\alpha*(1-s)*fee$. We compute the value of research, information, and price impact for each investor type as the average of the ratio of the coefficient of interest divided by an investor's sensitivity with respect to fees ($-\alpha$).

Table 7: Broker Choice - Heterogeneous Coefficients

	Mean	Std. Dev.
Fees	-464.90***	475.99
Price Impact:	-8.54***	206.37
Research		
Number of Analysts	0.028***	0.034
Number of Top Rated Analysts	0.078***	0.080
Information:		
Eigenvector Centrality	0.59***	0.59
Informed Broker	0.12***	0.10
Sector×Investor×Time Fixed Effects	X	
Broker×Investor Fixed Effects	X	
IV (Commissons)	X	
Observations	6,668,464	
Elasticity	0.54	0.56
Value of Research:		
Value of an Additional Analyst (bp)	0.78	1.81
Value of an Additional Top Analyst (bp)	1.99	6.58
Value of Information:		
Value of 1σ Increase in Eigenvector Centrality (bp)	1.56	6.18
Value of an Informed Broker (bp)	3.62	9.47
Value of 1σ Decrease in Expected Price Impact (bp)	3.50	161.5

Note: Table 7 displays the estimation results corresponding to our heterogeneous coefficient discrete choice broker model (eq. 9). The unit of observation is at the investor by broker by month by sector (6-digit GICS) over the period 1999-2014. We restrict our analysis to 247 investors where we observe at least 1,000 observations. 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 fees in percentage terms relative to the value of the transaction. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

In the bottom half of the table we interpret the coefficient estimates. Elasticity of demand is calculate as $-\alpha * (1 - s) * fee$. We compute the value of each independent variable as the ratio of the coefficient of interest divided by an investor's sensitivity with respect to fees ($-\alpha$).

Table 8: Research Related Soft-Dollars Relative to Management Fees

	Mean	SD	Percentile				
			10th	25th	50th	75th	90th
Soft-Dollars Per Trade (bp)	2.77	4.29	0.07	0.62	1.92	4.09	7.08
Annual Soft-Dollars (% of Annual Management Fees)	4.30	7.36	-2.12	0.15	2.26	7.33	13.98

Table 8 presents the distribution of the value of soft-dollar research payments on a per-trade basis (in bp) and annualized (% of management fees) for mutual funds in our sample. Observations are at the investor-by-year level. We calculate the value of soft-dollar research payments on a per-trade basis based on the compensating variation required if we were remove sell-side research from the market (eq. 10; Table 4). We calculate the annual value of soft-dollar research related payments as the average compensating variation at the investor-by-year level multiplied by how often the institutional investor turns over his/her portfolio. We express the annual value of soft-dollar research payments relative to annual management expenses. To account for outliers, we winsorize annual soft-dollars at the 2.5% level.