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THE VALUE OF INTERMEDIATION IN THE STOCK MARKET

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ABSTRACT

Brokers play a critical role in intermediating institutional transactions in the stock market. Despite the 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, access to research, and order flow information. Studying over 300 million institutional trades, we find that investor demand is relatively inelastic with respect to trading commissions and that investors are willing to pay a premium for access to formal (top research analysts) and informal (order-flow information) research. There is also 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. Using trader-level data, we find that investors are more likely to execute trades through intermediaries who are located physically closer and are less likely to trade with those that have engaged in misconduct in the past. Lastly, we use our empirical model to investigate soft-dollar arrangements and the unbundling of equity research and execution services related to the MiFID II regulations. We find that the bundling of execution and research potentially allows hedge funds and mutual funds to under-report management fees by 10%.

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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 and have subsequently 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.[2]

Figure 1 displays the share of institutional 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 institutional investors, despite the perceived growth of alternative trading venues.[3] Consistent with this trend, the number of registered equity traders in the U.S. has remained relatively constant since the financial crisis.

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, whose determinative factor is not just the lowest possible commission cost, but requires that "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."[4] In this pa-

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

[2] The Markets In Financial Instruments Directive (MiFID) II was rolled out on January 3, 2018. It applies to all European asset managers, but it has repercussions on global brokerage firms selling services to European clients. Prior to MiFID II, research costs were often 'bundled' into opaque transaction fees borne by funds' clients. MiFID II unbundling reform aimed to ensure that portfolio managers act in the best interests of their clients without undue influence by third parties. Investment managers are now required to pay for research separately from execution services, and either charge clients transparently or pay for research themselves.

[3] Our analysis focuses on asset managers, such as mutual funds, hedge funds, and pension funds, that trade at relatively low frequency. This in contrast to the recent work examining the growth and proliferation 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)).

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

per, we examine how investors make their trading 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 order-flow information? Understanding the drivers of execution decisions provides insight into how brokers create value for institutional investors and might be instrumental in guiding policy interventions.

A key challenge in studying these issues is a lack of data, since understanding these issues requires detailed information on brokerage firms and institutional trading patterns. Obtaining this information 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 details on both the institutional investors and brokerage firms involved in the transactions. Our primary 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 sample covers the period between 1999 and 2014 and includes trade-level data for institutional investors, accounting for up to 20% of the institutional trading volume in the U.S. stock market (Puckett and Yan (2011), Hu, Jo, Wang, and Xie (2018)). Importantly, we observe the identity of the investment manager placing the trade and the broker executing the corresponding trade.

We merge the Ancerno sample with rich brokerage firm-level data from several sources. To measure each broker's capacities in a given market and time, we merge Ancerno data 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 information from BrokerCheck. BrokerCheck is a website operated by the Financial Industry Regulatory Authority (FINRA), and the website contains a wealth of details on the universe of individuals registered in the securities industry (See Egan, Matvos, and Seru (2019) for further details), including 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. We examine an investor's trading decision process with a particular emphasis on *where* investors decide to execute their trades. 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 explicit trading costs (i.e. commissions/fees), implicit trading costs (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 trading network. The model allows us to quantify the factors driving execution decisions.

We estimate our discrete choice framework following the workhorse models used in the industrial organization literature (Berry (1994) and Berry, Levinsohn, and Pakes (1995)). Our setting and data is ideal for such estimation for several reasons. First, we observe individual institutional investors making tens of thousands of execution decisions. 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 commission/broker fees. If brokerage firms are able to flexibly adjust their fees in response to 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 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 costs paid by investors.

We first examine the price sensitivity of investors. The average broker 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 many other factors that influence broker choice.

As pointed out by Anand, Irvine, Puckett, and Venkataraman (2012), an important factor driving institutional trading decisions is the quality of execution offered by a broker. Brokers may differ in their ability to execute large trade orders without moving the market price of a stock. We measure these implicit trading costs at the trade-level as the price impact of the trade, i.e. 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 decrease in price impact is worth 7bps, which is equal to roughly one-half of a standard deviation in broker fees. This finding suggests that both explicit and implicit trading costs play an important role in execution decisions.

In addition to execution, brokers offer formal 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 broker fee for all of the services a broker offers. Our estimates indicate that investors are willing to pay a 10-15% higher broker fee (1-2bps relative to the value of the transaction) to have access to a research analyst and an additional 20-40% (3-5bps relative to the value of the transaction) to have access to a top analyst in the sector (as per Institutional Investor).

Brokers are also information hubs, because they are likely to have a more comprehensive view of market trends and investors' strategies, and institutional investors likely value this information. We measure order flow information in two ways. First, following Di Maggio, Franzoni, Kermani, and Sommavilla (2019) 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 15-40% (2-6bps relative to the value of the transaction) to execute a trade through a broker who has received privileged information about informed order flow. Second, following Di Maggio, Franzoni, Kermani, and Sommavilla (2019) we can capture the broker's access to information with its centrality in the network of relationships between managers and brokers. Like these authors, we measure a broker's centrality within the network based on its eigenvector centrality. Intuitively, a broker is more likely to be informed if it trades with multiple institutional investors, who are themselves more central in the market. We find that investors are willing to pay an additional 10-25% (1-3bps relative to the value of the transaction) to execute a trade through a broker that is more centrally located within the broker network by one standard deviation.

The central role of information in equity markets has helped lead to the proliferation of alternative trading systems (ATS) and dark pools (see Zhu (2014)). These non-exchange trading venues operated by brokerage firms help investors hide their order flow and provide access to alternative sources of liquidity. Using data from the Securities and Exchange Commission, we track the development of ATSs in our sample. As of 2000, essentially none of the brokerage firms in our sample operated ATS; however, by 2014, roughly 50% of trades were executed through brokers who had access to their own ATS and dark pools.[5] Our demand estimates suggest that investors are willing to pay an additional 15% (2bps higher relative to the value of the transaction) fee per trade in order to trade through a brokerage firm that operates an ATS.

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 through 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.[6] 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.[7] The

[5] As displayed in Figure 3.

[6] 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.

[7] A one percentage point increase in misconduct corresponds $-2.18 \times (1 - s)$ percent decrease in the broker's transac-

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 10% (1bp relative to the value of the transaction) more per additional year of trader experience. Lastly, we find evidence that investors prefer to trade through 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."[8] Moreover, this finding extends the evidence of local bias in asset management (Coval and Moskowitz (1999)) to the choice of trading intermediaries.

This rich setting also allows us to explore how the execution decisions and preferences vary across investors. In fact, we should not expect all institutional investors to weigh the different dimensions equally. For example, while we find that the average investor values sell-side equity research, we also find that roughly one-third of investors places 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 informed order flow. Similarly, we find that, as expected, index funds do not choose their brokers based on research, which is also useful in validating our empirical framework by making it less plausible for unobserved characteristics of the brokers to be driving our results.

Our estimates show that the ancillary services brokers provide create substantial value for investors. While 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 corresponding to MiFID II, European regulators mandate that brokers must unbundle their services. 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; however, it is usually challenging to quantify this type of under-reporting. One of the advantages of our paper is the possibility to exploit our framework to estimate the value of the unobserved soft-dollars that brokers receive as payment for research. Specifically, for each investment manager, we separately calculate the investment manager's shadow-value of broker-produced sell-side research following the methodology used in Petrin (2002).[9][10] Our esti-

tion volumes where s is the broker's current market share (Table 4). We calculate the marginal effect using the average market share in our sample ($s = 10\%$).

[8]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.

[9]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.

[10]In general, we study how MiFID II and unbundling impacts the use of soft-dollars, investment management fees,

mates suggest that if investment managers had to pay for research in terms of hard- rather than soft-dollars, investment management fees would be up to 10% higher. There is also substantial heterogeneity across managers; our estimates suggest that the use of soft-dollars potentially allows some firms to under-report management fees by more than 20%.

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) and 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 making 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.

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

and market transparency. There is also recent research examining the preliminary impacts of MiFID II on the supply of sell-side research (Fang, Hope, Huang, and Moldovan (2019); Guo and Mota (2019); Lang, Pinto, and Sul (2019)). Evidence from Guo and Mota (2019) suggests that the implementation of MiFID II led to a 7.45% decline in research coverage in Europe. While we study a different aspect of MiFID II, the finding that research coverage falls following the implementation of MiFID II is consistent with our empircal finding that roughly 10%+ of investment managers place no value on research (Section VI).

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 (2019)) and ongoing fire sales (Barbon, Di Maggio, Franzoni, and Landier (2019)). 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 bundling comes from the firm side as bundling 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 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.[11] Our analysis focuses on the former and more common in-house related soft-dollar payments. Using proprietary data, 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. While we focus on in-house soft-dollars instead of third party soft-dollar arrangements, we find similar costs/magnitudes as in their paper.

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 institutional investor's decision regarding *where* to execute her 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 j in industry sector k

[11] 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.

through brokerage firm l at time t is given by:[12]

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

Investors pay an investor-trade-broker-sector specific commission/broker fee f_{ijklt} for executing a trade through broker l, from which she derives dis-utility $\alpha_i f_{ijklt}$. 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, access to dark pools, and/or information. For example, some brokers may have more skilled traders than other firms and consequently provide better trade execution resulting in a lower transaction price (i.e. lower price impact). 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. Our framework allows for such differences. The vector X_{klt} 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 and other services that the investor can receive from the broker once a stable relationship is established similar to the framework proposed and studied in Goldstein, Irvine, Kandel, and Wiener (2009). 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, and an investor is likely to internalize these dimensions. 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 algorithms and 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 new algorithm) 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-

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

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

The units of eq. (1) are in terms of utils; however, by scaling eq. (1) we can interpret each coefficient in the utility function in terms of expected profits:

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

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 the present value of expected future profits.

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

$$\max_{l \in \mathcal{L}} E[u_{ijklt}]. \tag{2}$$

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 through firm l is given by

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

The above likelihood corresponds to the multinomial logit distribution and is the core of our estimation strategy below. Estimation of this demand framework is straightforward, and it allows us to measure how institutional investors trade-off broker-provided services. We describe estimation in Section IV.

Lastly, while we cast our framework in the context of an investor's decision regarding where to execute her trade *conditional* on the initial decision to trade a specific security, the model 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 investor 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 through. 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 brokers). 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 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. The data set consists of over 300 million trades. For each trade we observe the names of the parties involved (broker and investment manager), the security traded, execution price, and the fee. We restrict our attention to those observations where we observe complete trade information (parties involved, security, date, and broker fee) where the investor reported paying a fee to the broker.[13] We also focus our attention to those institutional investors that made at least 1,000 trades in the data set.The final data set covers 393 investment managers trading across 1,590 different brokers.

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 rather than to advertise their 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. It's worth noting that pension funds may instruct the managers in whom they have invested 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 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 clients as well as the respective returns are comparable to those reported in mandatory 13F filings. Estimates

[13] We drop observations where the investor does not report paying a positive broker 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.

suggest that trades recorded in Ancerno account for 10% to 19% of all institutional trading volume in the U.S. stock market (Puckett and Yan (2011), Hu, Jo, Wang, and Xie (2018)). The data is organized at different levels; at the trade-level, we know: the transaction date and time at the minute precision, the execution price; the number of shares that are traded, the side (buy or sell) and the stock CUSIP.

III.B Equity Research Data

To help examine the different factors driving an investor's 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.[14] 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 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).

[14]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.

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 of experience in the industry. FINRA also 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. 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.

Although we observe the identities of each trader, we do not observe the specific securities they trade. Consequently, we merge the BrokerCheck equities trader data with our Ancerno trade-level data at the brokerage firm-by-year level. In our analysis, we examine how much investment managers value various characteristics of a brokerage firms, including:the number of traders at the firm, average trader experience, and the percent of traders previously reported for misconduct. Using BrokerCheck data, we are also able to determine the physical office locations of the brokerage firm traders and many of the investors in our data set. We calculate the physical distance in miles between each broker-investor pair, using 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. While the average distance between an investor and a broker in our sample is 668 miles, 33% of our broker-investor trading pairs are within 100 miles of each other.

III.D Alternative Trading Systems/Dark Pool Data

A number of brokerage firms in our data set operate their own proprietary alternative trading systems (ATS) such as electronic communication networks (ECNs) and/or dark pools. These non-exchange trading venues operated by brokerage firms provide investors with an alternative mean to access liquidity in the market outside of traditional exchanges. We collect data on which brokerage firms in our data set operate their own ATS to help understand the value of these non-exchange venues. The SEC reports the names and initial filing dates of all active ATS at a semi-annual frequency.[15] Using these SEC filings, we construct a monthly panel of active ATS over the period 1999-2014. We manually match the ATS to the brokerage firms in the Ancerno data using firm

[15]The SEC started reporting this information as of September 2008: https://www.sec.gov/foia/ats/atslist0908.pdf [accessed September 19, 2019].

name. Many ATS are operated by full-service brokerage firms such as Goldman Sach's Sigma X dark pool, but there are also stand-alone ATS in our Ancerno data such as Direct Edge ECN.

As of 2014 there were 93 ATS registered with the SEC. One shortcoming of our data is that for trades executed through full-service brokerage firms that operate ATS, we do not observe whether the trade was executed through an ATS or on an exchange. We only observe whether the brokerage firm had access to its own ATS. For example, we observe whether an investor executed a trade through Goldman Sachs, but we do not directly observe whether the trade was executed through Goldman Sach's Sigma X dark pool or some other venue. Figure 3 displays the share of trades in our sample that were executed through a brokerage firm that has access to its own ATS over time. While there were few ATS in 2000, by the end of our sample, over half of the trades were executed through brokerage firms that had access to dark pools.

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 that of 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 that 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.[16]

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

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

[16]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 brokerages 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 maximum likelihood or other non-linear estimation methods.

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

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

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. (5) using linear regression where we include an investor-by-sector-by-time market fixed effect (μ_{ikt}) to absorb the non-linear term.[17] We estimate the linear specification

$$\ln s_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \mu_{ikt} + \xi_{iklt} \quad (6)$$

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 of our broker characteristics X_{klt} in the proceeding section. In our baseline specifications (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. 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 broker 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 that their 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 why researchers in the demand estimation literature to date have specifically been more concerned about the endogeneity of prices (broker 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

[17]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. (5) the market share of broker l in a given market (month-by-investor-by-sector) depends on the utility that 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 that the 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. (5), 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.

is unlikely that firms adjust their research coverage in response to time-varying demand shocks because the hiring process for research analysts is a lengthy and 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.

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.

Explicit Trading Costs: Broker Fees Brokers typically charge investors a fee for each share of stock traded. We measure the broker 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 transaction fee is 13 basis points (bp). Figure 2a displays the distribution of broker 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 broker fees translates to an annualized cost of 14bps ($\approx 2 \times 54\% \times 13$bp) relative to the fund's total assets.[18] 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 broker fees, fees would be correlated with the unobservable term ξ_{iklt}.

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

[18]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.

stock traded (see Goldstein, Irvine, Kandel, and Wiener (2009)).[19] Figure 2b displays the distribution of broker 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. For instance, a one cent increase in the fee per share is more costly when an investor is trading a stock priced at \$1 per share than when she is trading a stock priced at \$1,000 per share.

We exploit the institutional fee setting feature of the brokerage industry to construct an instrument for broker 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 through brokers who have analyst coverage in the corresponding sector and measure the value that investors place on those sell-side analysts.

Information Recent evidence has highlighted the role played by financial intermediaries in creating value through information production (Babus and Kondor, 2018; Barbon et al. 2019). Brokers may have access to additional information about market conditions, trends and specific stocks 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

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

information draw inspiration from Di Maggio, Franzoni, Kermani, and Sommavilla (2019). 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. All else equal, being connected to a more central manager leads to a higher centrality score for the broker. 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 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 (2019) study the role that 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 an 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 ($Informed_{klt-1}$).[20] This allows us to measure how informed order flow spills over to other investors.

Alternative Trading Systems and Dark Pools We control for whether a brokerage firm in our sample has access to its own alternative trading system (ATS) such as a dark pool. We construct the indicator variable ATS_{lt} which is equal to one if brokerage-firm l operates its own ATS at time t. An important caveat with our alternative trading system/dark pool variable is that it is measured at the broker-by-month level while our other brokerage firm characteristics are measured at the broker-by-month-by-sector level. Consequently, the variable ATS_{lt} is subsumed by our by broker-time fixed effects in our full specification. One related concern, which we discuss further below when interpreting our results, is that the variable ATS_{lt} could be correlated with other time-varying characteristics of a brokerage firm.

Implicit Trading Costs: Price Impact Implicit trading costs may arguably be just as important as explicit trading costs. Anand, Irvine, Puckett, and Venkataraman (2012) show that brokers differ in their execution quality in a persistent way. We measure the implicit trading cost of a trade using the implementation shortfall (Perold (1988), Wagner and Edwards (1993)). As described in Anand, Irvine, Puckett, and Venkataraman (2012), the execution shortfall reflects the bid-ask spread, the

[20]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.

market impact, and the drift in price. With this in mind, we call this variable price impact and define it as the stock price at which the trade was ultimately executed relative to the stock price at the time the order was placed,

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

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 indexes the stock, and t indexes 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 a handful of potential concerns with our price impact measure $Price\,Impact^*_{lkt}$ that merit further discussion. First, it is inevitably measured with noise. Our empirical measure of price impact reflects both the true variation coming from price impact as well as variation from changes in the underlying fundamentals from the stock. For example, even if markets were perfectly liquid, we would expect the execution price to potentially differ from the placement price due to the variation in fundamentals. 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 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 through 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:

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

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). To the extent 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. (6). 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 instrumenting both fees and expected price impact as described in Section IV. Lastly, in columns (3) and (4) we include broker and broker$\times$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 downwards. 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).[21]

[21] 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.

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 $\alpha(1 - s_{iklt})f_{iklt}$.[22] 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 suggests 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 services separate from trade 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 0.16 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 per trade in order to have access to a top equity research analyst, while having access to an additional 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 behave as if they are willing to pay a 40% (=5.35/13) higher fee, relative to the mean fee, to access a top equity research analyst.

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 next 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

[22]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. (4).

broker-by-sector-by-investor characteristic, it would have to be that index fund managers and hedge funds also place little value on that characteristic.

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 (2019) and Di Maggio, Franzoni, Kermani, and Sommavilla (2019) 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 through 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 through central brokers. The results in column (2) indicate that investors are willing to pay an additional 2.77bps per trade in order to trade through 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 through an informed broker, which is similar to and actually slightly higher than the value that 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 Access to Alternative Trading Systems/Dark Pools

In recent years, alternative trading systems account for almost half of all trading volumes in the US.[23] Revealed preference suggests that investors value these alternative non-exchange trading venues. We quantify this benefit in our analysis by including the dummy variable ATS_{lt} which indicates whether the brokerage firm operates an ATS, such as a dark pool, at time t. Table 2 presents the corresponding estimates. Note that because the variable ATS_{lt} naturally varies at the investor-by-month level, the variable is subsumed by the broker-by-month fixed effect in column (4). We estimate a positive and significant relationship between a brokerage firm's market share and whether it operates an ATS. The results in bottom half of Table 2 indicate that an investor

[23] https://www.cfainstitute.org/en/advocacy/issues/dark-pools [accessed 10/9/2019].

behaves as if she is willing to pay an additional 2-6bps in order to execute a trade through a brokerage firm that has had access to an alternative trading system/dark pool. One important caveat is that the variable ATS_{lt} varies at the broker-by-month level rather than the broker-by-sector-by-month level. Thus, one concern is that our variable ATS_{lt} captures other time-varying broker characteristics that are correlated with when a brokerage firm established an alternative trading system. In Section VI we explore how different investors value ATS to provide additional insight into this potential endogeneity concern.

V.E Implicit Trading Costs: Price Impact

Given the time and resources devoted by investors to 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 through a broker whose expected price impact is one standard-deviation (0.67%) lower. 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.

To the extent that expected price impact directly translates into higher execution costs, one might expect investors to trade off price impact and broker fees one-for-one. Recall that our estimate of investor's preference with respect to price impact likely suffers from attenuation bias because our measure of price impact reflects both variation in fundamentals and true price impact. Also, to extent that price impact is not perfectly observed and forecastable by investors, a Bayesian investor would find it optimal to place less weight on implicit trading costs relative to explicit costs.

To help address these potential measurement error and saliency issues, we examine an investors' sensitivity to large trading costs. Specifically, we re-estimate our baseline specification where we control implicit trading costs with the variable $LargePriceImpact_{lkt}$, which measures whether the price impact was greater than 0.25% (roughly the 50th percentile). We report the estimates in Table 3. The results in column (2) suggest that investors behave as though they are willing to pay an additional 34bps (=1.37/398) higher broker fee, relative to the value of the transaction, in order to avoid a large price impact of at least 0.25%. Given that the median (mean) large price impact is 0.46% (0.66%), this implies that investors trade off implicit and explicit trading costs almost one-for-one. The results suggest that investors avoid brokers with a track record of particularly poor execution, which may be more salient and predictable than average execution.

V.F 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.[24] 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 4 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 0.45bps decrease 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 through firms that employ more experienced traders. The results in column (2) indicate that, on average, investors are willing to pay an additional 0.82bps to trade through a firm whose traders have an additional year of experience. However, we find evidence of a non-linear relationship. Investors prefer to trade through 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 firms' 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 5. The results indicate that investors prefer to trade through 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 10bps more per trade in order to trade through 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

[24] We are able to match only half of the Ancerno data set with the BrokerCheck trader-level data because BrokerCheck covers t6he period 2005-2018 whereas Ancerno covers the period 1999-2014.

person. These results also suggest that investors strongly prefer to trade through 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."[25] 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. However, in practice, different investors are likely to value different dimensions differently. For example, an S&P 500 index fund manager may be extremely price sensitive relative to a hedge fund or active mutual fund manager. Similarly, an S&P Index fund manager 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 for these difference services at the investor-level.

VI.A Estimation

We re-estimate our baseline specification (eq. 6) 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, 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 $\binom{\alpha_i}{\beta_i} = \binom{\alpha}{\beta}$. To implement our specification with heterogeneous preferences we estimate the following regression at the investor-level:

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

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. (7) 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

[25]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.

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 that 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. (7) at the investor-level where we restrict our sample to those 247 out of 393 investors that have at least 1,000 observations (sector-by-month-by-broker level).

VI.B Results

We estimate the preferences for each investor and report the distribution of estimated preferences across investors in Table 6. The mean preference parameters from our heterogeneous preferences specification are similar to the baseline estimates reported in Table 2. Consistent with our previous results, we find that the average investor values competitive implicit and explicit trading costs, research, information (eigenvector centrality and order flow information), and access to dark pools.

We also find persistent heterogeneity in preferences across investors, and we are able to reject the null hypothesis that investors have homogeneous preferences for each broker characteristic. We display the corresponding distribution of preferences in Figure 4 panels (a)-(g). The results suggest that there is substantial heterogeneity across investors. For example, while the average elasticity of demand in our sample is 0.54, Figure 4a indicates that some investors have demand elasticities of less than 0.2 while others have demand elasticities near one. We also find that there is substantial heterogeneity in how investors value sell-side research (Figures 4b and 4c). While the average investor values sell-side research, Figure 4c indicates that many (10%+) investors place no value on top analysts.

One important caveat is that for some broker characteristics, such as implicit trading costs, we have limited power to precisely estimate investor-specific preferences. While we are able reject the null hypothesis that investors have the same preferences with respect to expected price impact, the corresponding F-test indicates that measurement error accounts for roughly half of the estimated variation in the investor-specific coefficients corresponding to expected price impact (Figure 4g).[26]

To help understand how preferences vary across investors, we examine how preferences vary with observable investor characteristics. Specifically, we project our investor-specific preference

[26]Under the assumption that the variance of the estimation error is homoskedastic, the term $\alpha = \frac{F-1-\frac{2}{k-1}}{F}$, where F is the F-test statistic corresponding to the joint test that investors preferences with respect to expected price impact are homogeneous and k is the number of investors, measures how much of the variation in the distribution estimated coefficients with respect to expected price impact is driven by true underlying differences across investors versus measurement error (Casella (1992)).

parameters (α_i, β_i) on a vector of investor-specific characteristics D_i

$$\beta_i = \Gamma D_i + \eta. \tag{8}$$

The vector D_i captures the observable 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).[27],[28]

We report the corresponding estimates in Table 7. The estimates help provide insight into how preferences vary across investors. For example, the preferences of hedge funds managers appear to be distinct from other institutional investors. Hedge fund managers do not appear to value sell-side research, placing little weight on the total number and the number of top research analysts a brokerage firm employs (columns 2 and 3). This result is intuitive, as hedge funds create value by conducting their own investment research and producing information in financial markets. Conversely, hedge funds appear to place greater value on informal information regarding order flow (column 5). While our previous results indicate that investors, on average, value brokers that are more central in the trading network, we find that hedge funds actually prefer to trade through less central brokers (column 4). One potential explanation for this finding is that hedge fund managers may be more concerned about concealing order flow and about brokers leaking a hedge fund's trades (Barbon, Di Maggio, Franzoni, and Landier (2019); and Di Maggio, Franzoni, Kermani, and Sommavilla (2019)). Thus, a hedge fund manager may prefer to trade through more peripheral brokers, conditioning on the broker possessing order flow information.

Index fund managers also have distinct preferences relative to other investors. Similar to hedge fund managers, index fund managers appear to place no value on sell-side research which is intuitive given that index fund managers have no use for research. We also find some evidence that index fund managers are among the most price sensitive investors with respect to both explicit and implicit trading costs (columns 1 and 7), although the point estimates are marginally insignificant at the 10% level.

Overall, the results suggest that accounting for investor heterogeneity in brokerage markets is of first-order importance, especially when examining how investors value the ancillary services, such as sell-side research that brokerage firms offer. Accounting for this heterogeneity has important implications for how the proposed MiFID II regulations will impact investors.

[27]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.

[28]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.

VII Soft-dollars and Management Fees

Brokers traditionally provide bundled services to institutional investors, combining execution, research and other brokerage services. Over the past 20 years, there has been a push among institutional 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 investment managers to pay for research and other brokerage services with soft-dollars through execution fees rather than to directly pay for these services with hard-dollars. Soft-dollar transaction fees are not reported in the fund's expense ratio but are subtracted from the fund's returns.[29] 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 investment manager 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 investment manager 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. 7) allow us to quantify soft-dollar in-house research related payments in the brokerage industry. Our empirical estimates measure how each investment manager precisely values the in-house research produced by brokers, and how much more an investment manager 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 potentially be if investment managers were to include the value of soft-dollar in-house research related payments in their management fees. Such analysis would not be possible without our empirical model. For example, simply looking at the heterogeneity in fees (Figure 2) would be insufficient because we do not know if an investment manager pays a higher execution cost because the manager places a high value on research or because the manager is worse at execution. Our analysis allows us to precisely quantify soft-dollar research payments in terms of hard-dollars.

VII.A Quantifying the Soft-Dollars

We use our empirical estimates to quantify the total value investment manager 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.

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

The compensating variation tells us how much institutional investors would be willing to pay in hard-dollars to have access to sell-side research. In this sense, compensating variation represents an upper-bound on how much management fees are currently under-reported due to soft-dollar transactions. 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.

Importantly, the compensating variation calculation is inherently a partial equilibrium calculation where the characteristics of brokers are held fixed. If regulators forced investors to pay for research with hard-, rather than soft-, dollars, the price of research in 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. To this end, compensating variation is informative of an investment manager's subjective value of research and provides an upper bound on how much management fees are currently under-reported due to soft-dollar transactions.

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

$$CV_{ikt}^{Research} = \frac{\ln\left(\sum_{l\in\mathcal{L}_{ikt}} exp(\overline{u}_{iklt})\right)}{\alpha_i} - \frac{\ln\left(\sum_{l\in\mathcal{L}_{ikt}} exp(\overline{u}_{iklt}^{No\,Research})\right)}{\alpha_i} \tag{9}$$

where $\overline{u}_{iklt} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt}$ is the average utility derived by investment manager i from trading in sector k with broker l at time t and $\overline{u}_{iklt}^{No\,Resarch} = \overline{u}_{iklt} - X_{klt}^{Research}\beta_i^{Research} = -\alpha_i f_{iklt} + X'_{klt}\beta_i + \mu_{ilt} + \xi_{iklt} - X_{klt}^{Research}\beta_i^{Research}$ is the average utility derived by investment manager 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 investment manager 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. 7) we calculate compensating variation at the investor-by-market level.[30]

[30]Notice that in our demand specification we can write an investor's 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

VII.B Results

Figure 5 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 investment manager would be willing to pay an additional 3bps per trade in order to have access to sell-side research. Again, the value of research varies dramatically across the population of investment manager, 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 5, Table 8).

We can use the compensating variation estimates to provide an estimate of the upper bound on how much higher reported management fees would be if investment managers had to pay for research with hard-dollars. Compensating variation tells us the investment manager's perceived value of the research that they consume through soft-dollar payments 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 them by the fraction of an investment manager's portfolio that is traded in a given year (the investment manager's portfolio turnover times two).[31],[32] Lastly, we compare the annualized implied research costs relative to the fund's annual management fees to determine how much investment managers under-report management fees relative to the value they extract from soft-dollar research payments:

$$\frac{Annual\, Soft\, Dollars_{lt}}{Management\, Fees_{lt}} = \frac{\bar{CV}_{it}^{Research} \times Portfolio\, Turnover_{it} \times 2}{Management\, Fees_{t}}. \tag{10}$$

Figure 6 and Table 8 display our estimates of how much higher reported management fees would potentially be if investment managers had to explicitly pay research payments in hard dollars rather than paying for them through soft dollars. Specifically, Figure 6 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 reported management fees would be 4% higher if investment

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.

[31]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.

[32]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 that 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).

managers had to pay for the value of research they consume with hard dollars. Again, there is substantial heterogeneity across investors. While management fees are not under-reported for 25% of our sample ($\frac{Annual\,Soft\,Dollars_{lt}}{Management\,Fees_{lt}} < 0.25\%$), they are under-reported by more than 20% by some investment managers. For the investment managers in the top quartile, reported management fees would be 15% higher if the funds had to pay for the research in hard-dollars.

Because larger funds tend to place a higher value on research (Table 7), the results are even more stark when we calculate the amount of under-reporting weighted by assets under management (AUM), which may be the more relevant metric from an end-investor's or policymaker's perspective. The third row of Table 8 displays the distribution of the value of soft-dollars relative to management fees weighted by AUM. Overall, the results suggest that management fees would be 10% higher if investment managers had to pay for the value of research they consume with hard-dollars.

The evidence suggests that for many firms in our sample, the value of soft-dollar research related payments is substantial. Since the impetus behind MiFID II and its requirement for the unbundling of the services provided by brokers is to limit the use of soft-dollars and improve market transparency, our results suggest that its effect might be significant in terms of how the overall cost of delegated asset management will change . Furthermore, one aspect emerging from our analysis that is often overlooked is that the effect of this regulation is likely to be uneven, as some funds are likely to be significantly more affected than others due to their tendency to compensate brokers for their research with trading commissions.

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 better understanding this issue and estimating the value that brokers 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 50% more per trade in order to access 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 suggest that investment management fees would be 10% higher if investment managers are forced to pay for the value of research that they consume in hard- rather than soft-dollars. Overall, our results help explain why high-touch broker trading remains prominent in institutional equity markets.

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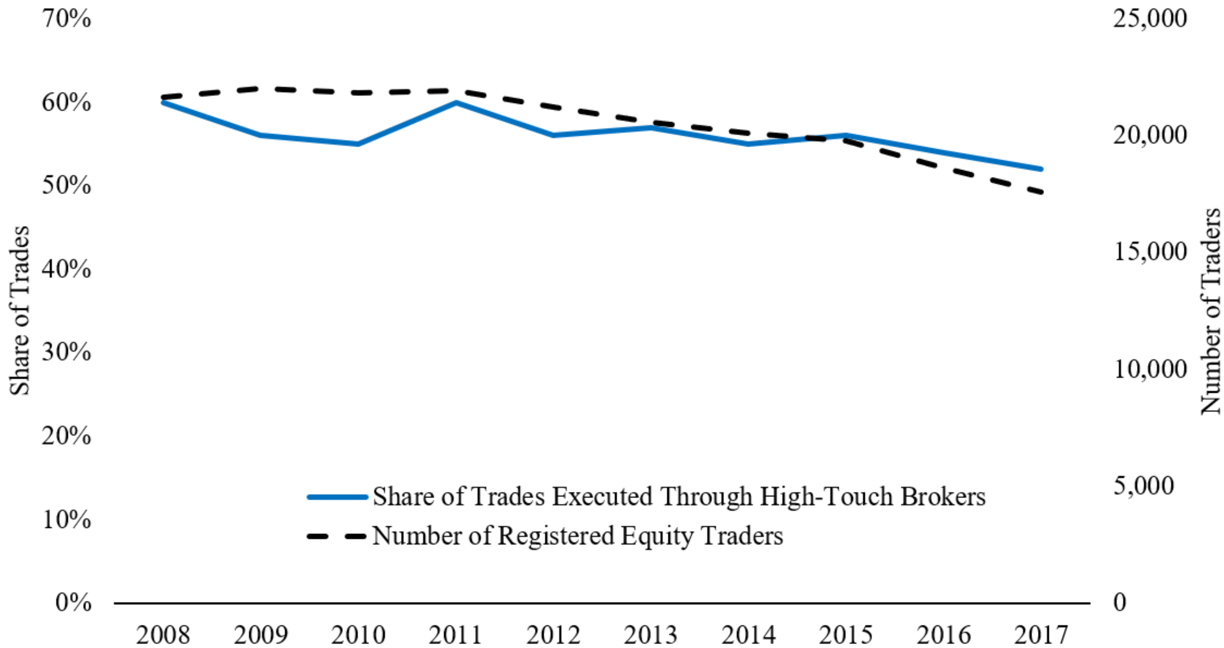
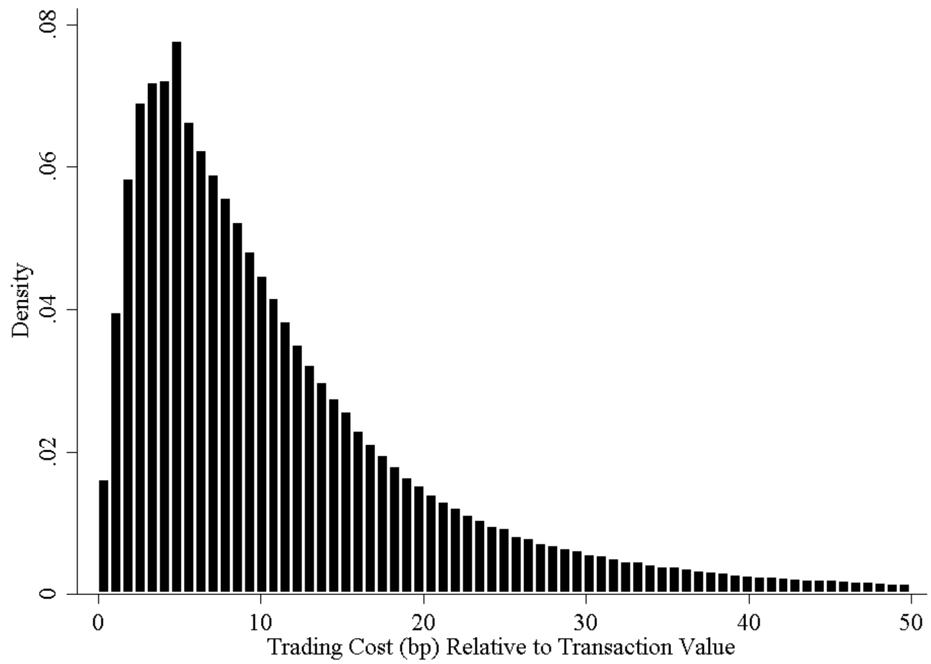
Figure 1: Share of High-Touch Broker Trades and the Number of Equity Traders in the U.S.



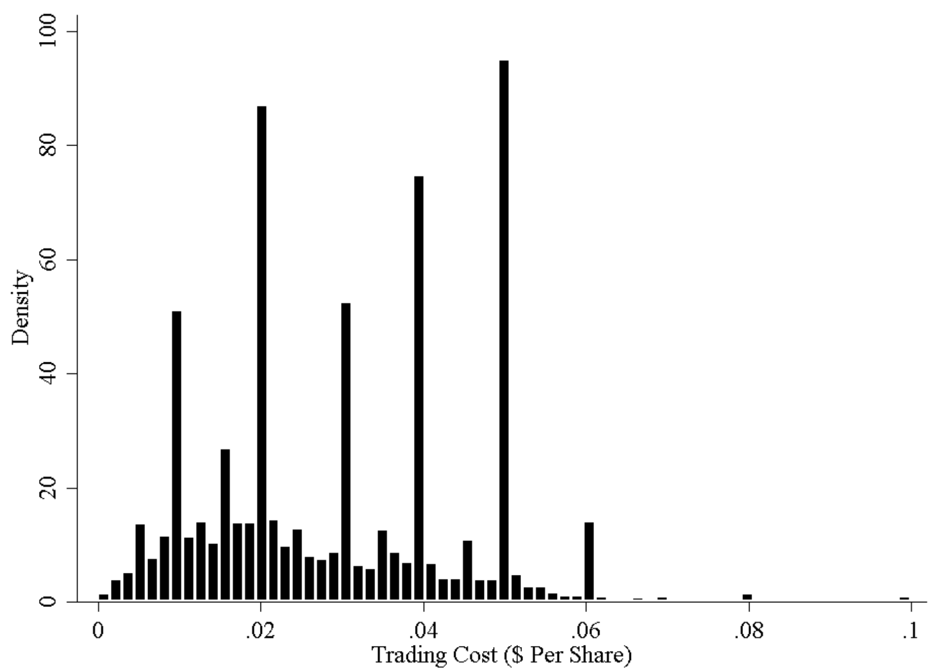
Note: The solid blue line displays the share of single-stock trades executed with high-touch broker sales traders. Data on trade execution comes from survey data conducted and reported by Greenwich Associates in the Greenwich Associates US Equity Investors Survey (2015-2017). The dashed black line displays 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)

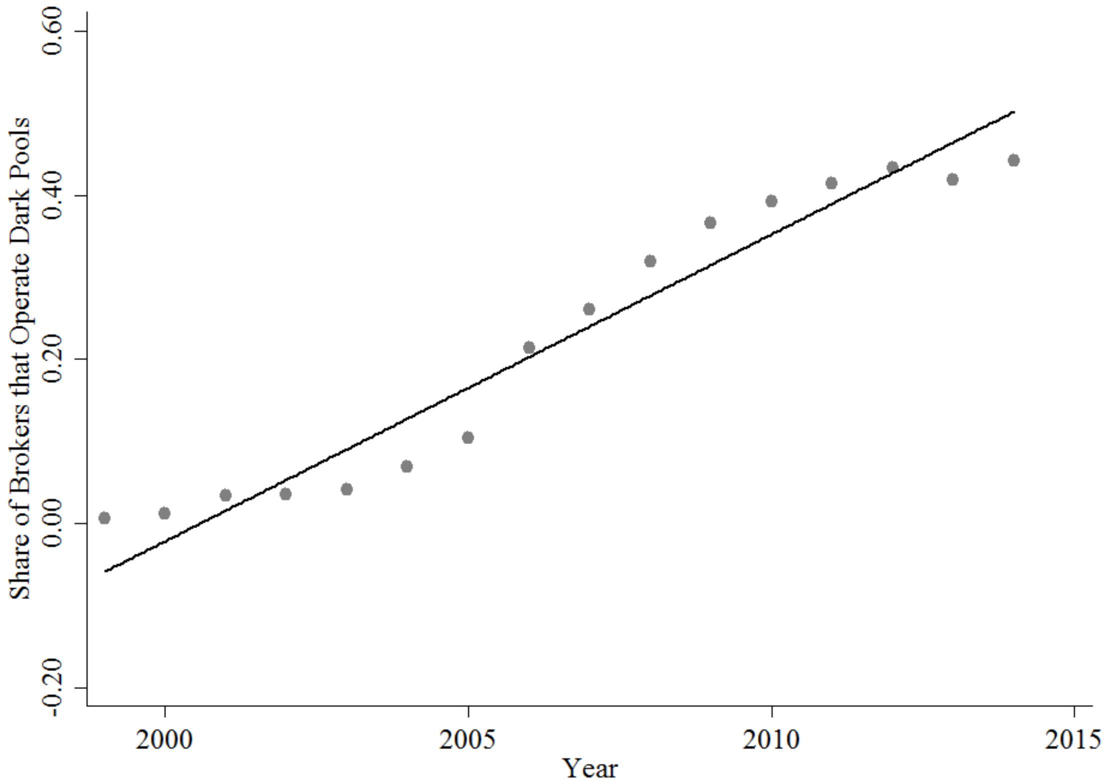


(b) Fees ($ per Share)



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 averaged at the investor-by-broker-by-sector-by-month level which is the unit of observation in our main analysis.

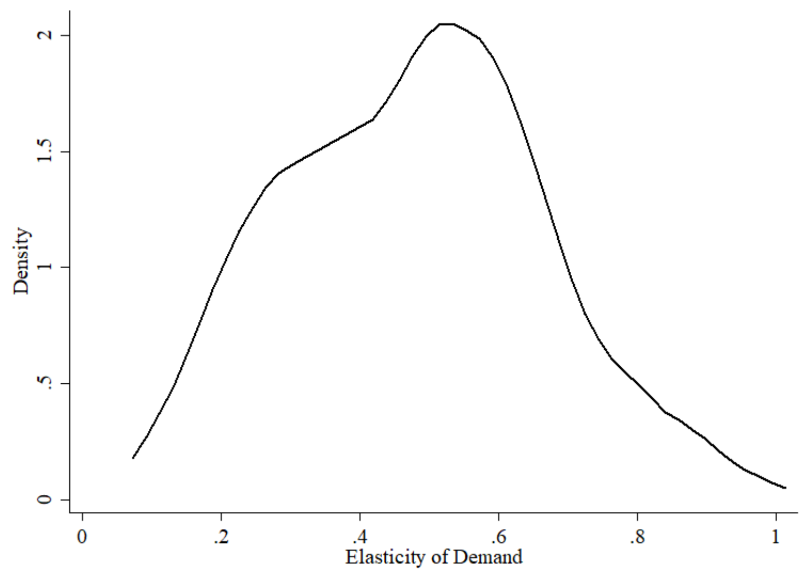
Figure 3: Share of Brokers that Operate Dark Pools Over Time



Note: The figure displays a binned scatter plot of the share of brokers that operate alternative trading systems/dark pools over time. Observations are at the investor-by-broker-by-sector-by-month level which is the unit of observation in our main analysis.

Figure 4: Preference Heterogeneity

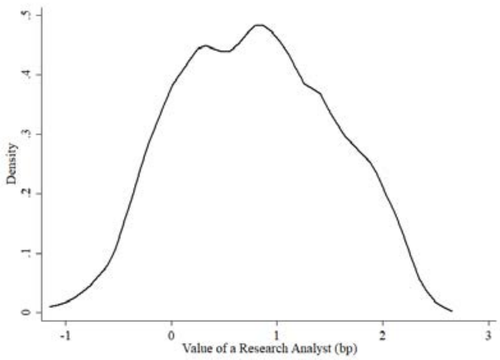
(a) Elasticity of Demand



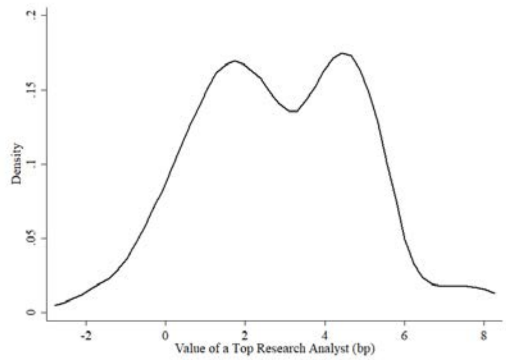
Note: Figure 4 panels (a)-(g) display the estimated distributions of demand elasticities, value placed on an additional Research Analyst, value placed on an additional Top Research Analyst, value of a 1 standard deviation increase in broker Eigenvector Centrality, the value of trading with an "informed" broker, the value of trading with a brokerage firm that operates an alternative trading system/dark pool (ATS), 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 6. 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, ATS access, 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 4: Preference Heterogeneity (Continued)

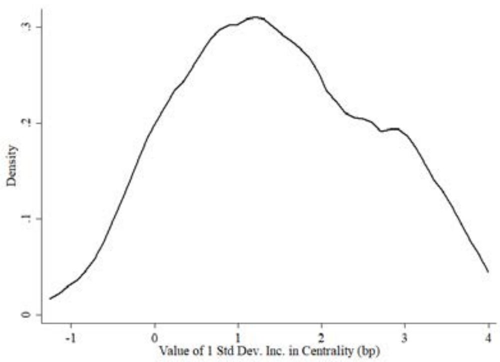
(b) Value of an Additional Analyst (bp)



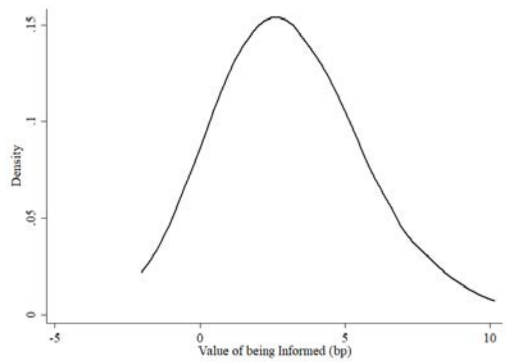
(c) Value of an Additional Top Analyst (bp)



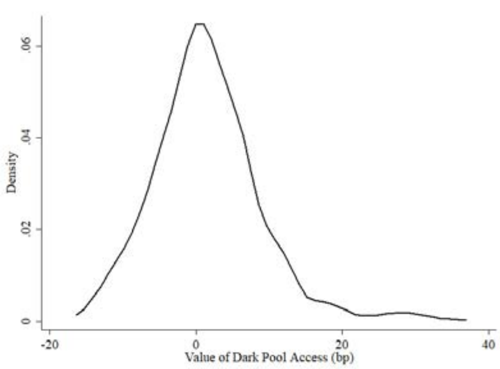
(d) Value of 1 SD Inc. in Broker Centrality (bp)



(e) Value of Information (bp)



(f) Value of Access to an ATS/Dark Pool



(g) Price Impact

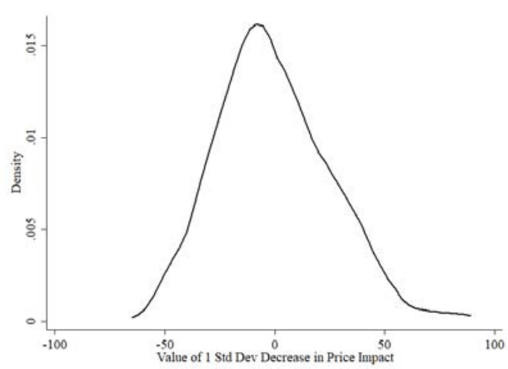
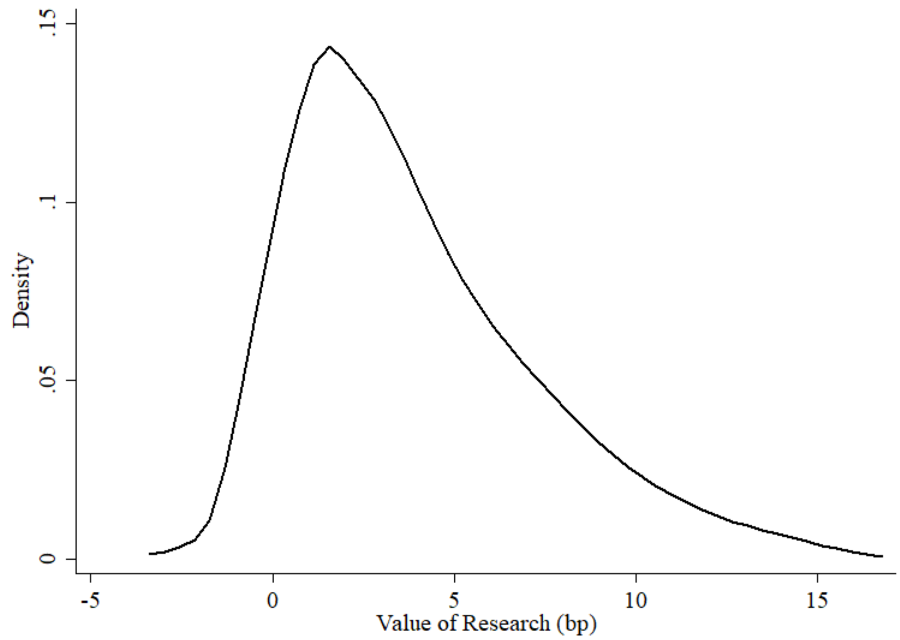
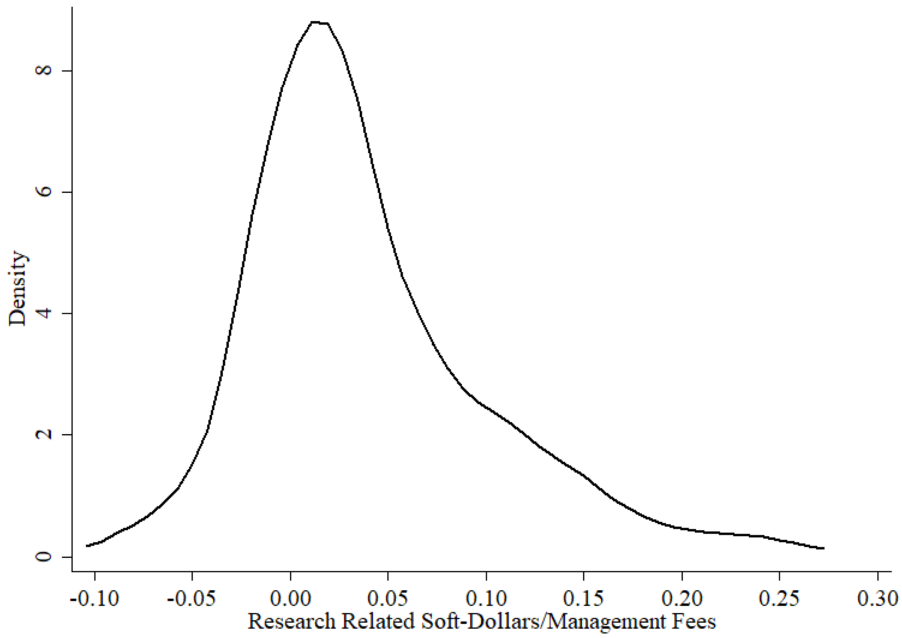


Figure 5: Total Value of Research



Note: The figure presents the distribution of compensating variation if we were to remove sell-side research from the market. The compensating variation indicates how much each investor would need to be compensated on a per-trade basis to make them indifferent between a regime with and without sell-side research. We compute the compensating required for each investor at the market level according to eq. (9). Observations are at the investor-by-month-by-sector level. The above figure displays the distribution truncated at the 1% and 99% level.

Figure 6: 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 to remove sell-side research from the market (eq. 9; Table 5). 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. The above figure displays the distribution truncated 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%
Access to an ATS/Dark Pool	7,224,298	25.59%	43.63%
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	7,224,298	0.21	0.41
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	-151***	-411***	-401***	-402***
	(4.32)	(7.85)	(7.02)	(6.94)
Access to an ATS/Dark Pool	0.10***	0.082***	0.10***	
	(0.029)	(0.029)	(0.026)	
Price Impact:	3.26***	-44.3**	-21.7*	-26.0**
	(0.35)	(19.3)	(12.6)	(12.7)
Research:				
Number of Analysts	0.067***	0.070***	0.032***	0.035***
	(0.0036)	(0.0037)	(0.0024)	(0.0017)
Number of Top Rated Analysts	0.15***	0.15***	0.068***	0.065***
	(0.010)	(0.011)	(0.0061)	(0.0043)
Information:				
Eigenvector Centrality	1.27***	1.14***	0.51***	0.31***
	(0.064)	(0.066)	(0.039)	(0.045)
Informed Broker	0.30***	0.25***	0.12***	0.10***
	(0.016)	(0.016)	(0.0070)	(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	0.268	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)	4.44	1.70	0.80	0.87
Value of an Additional Top Analyst (bp)	14.37	5.35	2.49	2.49
Value of Information:				
Value of 1σ Increase in Eigenvector Centrality (bp)	8.41	2.77	1.27	0.77
Value of an Informed Broker (bp)	19.87	6.08	2.99	2.49
Value of Access to a ATS/Dark Pool (bp)	6.62	2.00	2.49	
Value of 1σ Decrease in Price Impact (bp)	-1.45	7.22	4.63	4.33

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the investment manager-by-broker-by-month-by-sector (6-digit GICS) level 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 this instrument is that while brokerage firms charge investment managers on per-share basis which is relatively sticky, investment managers are more concerned about 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 calculated 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 × 0.067/151 = 4.44bps.

Table 3: Broker Choice and Large Implicit Trading Costs (Large Price Impact)

	(1)	(2)	(3)	(4)
Fees	-151***	-398***	-400***	-402***
	(4.31)	(7.92)	(7.05)	(6.98)
Large Price Impact	0.028***	-1.37***	-0.70***	-0.67***
	(0.0063)	(0.20)	(0.15)	(0.17)
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		5,100	2,000	740
Observations	6,484,127	5,756,568	5,756,564	5,755,998
R-squared	0.304	0.186	0.276	0.297
Mean Elasticity with Respect to Fees	0.18	0.47	0.47	0.47
Value of a Large Price Impact (bp)	1.85	-34.42	-17.50	-16.67

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the investment manager-by-broker-by-month-by-sector (6-digit GICS) level 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 this instrument is that while brokerage firms charge investment managers on per-share basis which is relatively sticky, investment managers are more concerned about the cost of the trade relative to the value of the transaction. Large Price Impact measures whether the price impact was greater than 0.25% across all trades in the sample. The median and average price impact of a Large Price Impact trade is 0.46In the bottom half of the table we interpret the coefficient estimates. Elasticity of demand is calculated 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 avoiding a large price impact in column (2) -1.37/398 = 34bps.

Table 4: Broker Choice and Trader Characteristics

	(1)	(2)	(3)	(4)
Fees	-481***	-482***	-482***	-482***
	(10.3)	(10.4)	(10.3)	(10.4)
Trader Characteristics:				
Misconduct	-2.17**			-1.80*
	(1.01)			(1.03)
Trader Experience		0.24***		0.23***
		(0.040)		(0.041)
Trader Experience^2		-0.0086***		-0.0083***
		(0.0014)		(0.0015)
Number of Traders (100s)			-0.026	0.038
			(0.045)	(0.051)
Number of Traders$^2 (100s)$			-0.0016	-0.0059
			(0.0037)	(0.0042)
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	0.294	0.295	0.293
Mean Elasticity	0.57	0.57	0.57	0.57
Value of Trader Characteristics:				
1pp Inc. in Misc. (bp).	-0.45			-0.37
1 Year Inc. in Trader Experience (bp):		0.82		0.76
100 Inc. in Number of Traders			-0.61	0.54

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the investment manager-by-broker-by-month-by-sector (6-digit GICS) level 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 this instrument is that while brokerage firms charge investment managers on a per-share basis, which is relatively sticky, investment managers are more concerned about 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, Informed, and ATS. 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 calculated 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 (-α). For example, we calculate the value of a 1pp increase in misconduct in column (1) as 10,000 $\times$ 2.17/481$\times$-1.00% = -0.45bps. We calculate the marginal value of a year of Trader Experience at the average value of Trader Experience (11.65 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 5: Broker Choice and Distance

	(1)	(2)	(3)	(4)
Fee	-146***	-401***	-400***	-397***
	(7.59)	(11.5)	(9.85)	(9.59)
Close Distance (Less than 100 miles)	0.40***	0.41***	0.33***	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	0.300	0.282	0.308	0.341
Mean Elasticity	0.18	0.47	0.47	0.47
Value Being Less than 100 miles (bp)	27.40	10.22	8.25	8.82

Note: The table displays the estimation results corresponding to our discrete choice broker model (eq. 6). The unit of observation is at the investment manager-by-broker-by-month-by-sector (6-digit GICS) level 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 this instrument is that while brokerage firms charge investment managers on per-share basis, which is relatively sticky, investment managers are more concerned about 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, Informed, and Dark Pool. 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 calculated 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 × 0.41/146× = 27.4bps.

Table 6: Broker Choice - Heterogeneous Coefficients

	Mean	Std. Dev.	F Stat.
Fees	-463.73**	475.43***	71.4
Access to ATS/Dark Pool	0.0625***	0.40***	23.9
Price Impact:	-10.70***	216.68***	2.08
Research			
Number of Analysts	0.028***	0.033***	12.8
Number of Top Rated Analysts	0.079***	0.080***	11.6
Information:			
Eigenvector Centrality	0.59***	0.59***	12.8
Informed Broker	0.12***	0.10***	7.31
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)	0.81	1.81	
Value of an Additional Top Analyst (bp)	2.78	7.13	
Value of Information:			
Value of 1σ Increase in Eigenvector Centrality (bp)	1.52	5.47	
Value of an Informed Broker (bp)	3.57	9.96	
Value of Access to a ATS/Dark Pool (bp)	3.11	27.99	
Value of 1σ Decrease in Expected Price Impact (bp)	3.58	160.84	

Note: Table 6 displays the estimation results corresponding to our heterogeneous coefficient discrete choice broker model (eq. 7). The unit of observation is at the investor-by-broker-by-month-by-sector (6-digit GICS) level 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. For each broker characteristic, we report the F Statistic corresponding to the null hypothesis that all investors have the same preferences over the given broker characteristics. 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 calculated 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 7: Investor Preferences by Type of Investor

	Fees (1)	Analyst (2)	Top Analyst (3)	Centrality (4)	Informed (5)	Dark Pool (6)	Price Impact (7)
Hedge Fund	135	-0.0075	-0.034**	-0.41***	0.085***	0.0040	75.3
	(97.7)	(0.0059)	(0.014)	(0.11)	(0.027)	(0.075)	(46.1)
Index Fund	-229	0.0013	-0.056	0.50	-0.049	-0.028	-199
	(259)	(0.022)	(0.040)	(0.67)	(0.064)	(0.15)	(155)
Large Investor	-92.4	0.033***	0.067***	0.34***	0.057***	0.056	-54.8
	(104)	(0.0060)	(0.013)	(0.084)	(0.015)	(0.067)	(40.4)
High Performance	61.5	0.0046	0.0015	0.30***	0.0027	0.12*	-27.8
	(79.4)	(0.0070)	(0.016)	(0.12)	(0.016)	(0.066)	(35.9)
High Churn	130	-0.0015	0.031*	0.057	0.038**	-0.023	43.6
	(199)	(0.0087)	(0.017)	(0.076)	(0.017)	(0.073)	(41.3)
Constant	-533***	0.0022	0.0080	0.21*	0.023	-0.019	4.09
	(166)	(0.0078)	(0.015)	(0.11)	(0.016)	(0.068)	(45.3)
Observations	247	247	247	247	247	247	247
R-squared	0.033	0.146	0.187	0.207	0.194	0.025	0.044

The table presents the results corresponding to a linear regression (eq. 8) where we examine how investor preferences vary with observable investor characteristics. Observations are at the investor level and the dependent variable in each column corresponds to the investors' preferences β_i for a given broker characteristic. The estimates of investor preferences correspond to the results reported in Table 6. Because the dependent variable is estimated from the data, we weight observation based on the number of observations we have for each investor. To account for outliers, we winsorize the estimated parameters at the 1% level. The independent variables Hedge Fund, High Churn (above average number of trades), High Performance (above average returns), and Large Investor (above average size) are all dummy variables. The variable Index Fund is between zero and one and indicates whether the investor operates one or more index funds. Specifically, we calculate index manually by searching 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. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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

	Mean	SD	Percentile				
			10th	25th	50th	75th	90th
Soft-Dollars:							
Per Trade (bp)	2.82	4.21	0.09	0.67	1.99	4.15	7.14
Annual (% of Management Fees)	4.23	7.54	-2.17	0.15	2.27	7.36	13.83
Annual (% of Management Fees) Weighted by AUM	9.87	9.01	0.08	2.28	7.80	14.98	26.64

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 the investment managers in our sample. Observations for soft-dollars per trade are at the investor-by-month-by-sector level, matching the unit of observation corresponding to our estimates reported in Tables 2-6. 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. 9; Table 5). Observations for annual soft-dollars are at the investor-by-year level. 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. In the final row, we calculate the distribution of the annual value of soft-dollar payments weighted by the investment manager's assets under management.