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The relevance of broker networks for information diffusion in the stock market☆

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ABSTRACT

This paper shows that the network of relationships between brokers and institutional investors shapes information diffusion in the stock market. Central brokers gather information by executing informed trades, which is then leaked to their best clients. After large informed trades, other institutional investors are significantly more likely to execute similar trades through the same broker, allowing them to capture returns that are twice as large as their normal trading performance. Also indicative of information leakage, the clients of the broker employed by activist investors to execute their trades buy the same stocks just before the filing of the 13D.

1. Introduction

How information is generated by market participants, disseminated, and finally incorporated into prices has been the subject of extensive literature in financial economics and remains one of the key questions for understanding how financial markets operate. Theoretical contributions on this topic date back to at least Grossman and Stiglitz (1980) and Kyle (1985); they have mainly focused on the strategic interaction between informed and uninformed traders. However, this interaction is far from happening in a vacuum, as financial markets are characterized by layers of intermediation and by a network of relations in which investors operate. Specifically, institutional investors routinely make use of brokers to execute their trades, and

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the brokers' role in disseminating the information that they acquire from their clients is at best unclear. Brokers' practice of selling order flow and the regulatory scrutiny about potential information leakage provide anecdotal evidence for the conjecture that brokers play a pivotal role in directing the information flow in the market.[1] This paper shows that brokers indeed play a key role in shaping information diffusion in the stock market.

Although information about prices is readily disseminated in equity markets, brokers' vantage points might allow them to extrapolate the informational content of an order and to anticipate the future behavior of prices. Moreover, some brokers have easier access to information than others. In particular, central brokers-those that are pivotal in the network of trading relations-are in a better position to observe the informational flow than peripheral ones. Then, brokers might have an incentive to extract these informational rents by communicating and spreading the information to their clients.

These considerations raise the question of how the network of relationships between brokers and investors influences market outcomes. Specifically, are the investors that are trading through central brokers able to generate higher returns thanks to the brokers' access to order flow information? What role do brokers have in affecting how information is incorporated into prices? This paper investigates these questions by exploiting institutional trade-level data, which provide information on the trades submitted by a significant sample of fund managers, including the identity of the broker intermediating the trades.

We motivate our analysis with results showing that trades channeled through central brokers earn significantly positive abnormal returns. Intuitively, if brokers have access to better information, the trades they intermediate should be, on average, more profitable. Our strategy is twofold. First, we construct monthly portfolios based on brokers' centrality. One advantage of this methodology is the ability to report the economic significance of the brokers' centrality for investors in a transparent way. We compute the monthly returns of the high-minus-low centrality portfolio and regress them on common risk factors. We find that this portfolio generates a significant alpha of about 40 basis points per month.

A potential concern is that brokers that are more central in the network also differ in other important characteristics from less central brokers; for instance, one could imagine better managers being more likely to trade with central brokers or central brokers being specialized in more illiquid stocks. To address these concerns, our second set of results takes advantage of the depth of our data. We find that trades channeled by central brokers tend to outperform those made through the peripheral ones, even when we consider the same stock traded by the same manager in the same timeframe, i.e., controlling for stock-manager-time fixed effects. This evidence strongly suggests that the main results are not fully explained by the fact that different brokers might trade stocks with different characteristics.[2]

Having established that trades executed through central brokers generate abnormal returns, which are not explained away by controlling for managers, stocks, or brokers characteristics, we investigate the source of these returns. Our tests are inspired by the recent theoretical studies of Babus and Kondor (2016) and Yang and Zhu (2016) that suggest a potential channel: by observing a larger and more informed order flow, central brokers can learn faster from the transactions they execute.[3] In other words, when an informed trader submits an order through a broker, the broker can then exploit its informational rent by disseminating this information to other clients, who would then earn higher returns by imitating the informed trader strategy.

This information channel has several implications, which we formally test. The first implication is that, if central brokers disseminate the information contained in informed trades, other traders should imitate the informed ones. To test this hypothesis, we identify informed trades in two ways. First, we investigate large trades executed by hedge funds (originators): we find that these large trades are profitable and anticipate a move of asset prices that is not followed by a reversal even after several months, which strongly suggests that these trades carry fundamental information. Second, we focus on the trades executed by activist investors as reported on their 13D forms and analyze the trading strategies of the other clients of the broker employed by the activist before the 13D is filed.

Our first main result is that other investors (followers) are significantly more likely to trade with the same broker in the same direction of the large informed trade while the broker is still executing the originator's order. These effects are more pronounced when the large order goes through a central broker, suggesting that central brokers are more likely to pass along the information about the large trade to other investors. This is probably because central brokers both have better access to information and are more likely to trade with hedge funds and other active managers who have the ability to act upon the information provided by the broker. Furthermore, another implication of the information channel is that if brokers have access to superior information, they should release it selectively in a way that allows them to extract the highest rents. Based on this logic, we find that the best clients of the broker, those generating a large share of its business, are significantly more likely to benefit from this information.

We also test whether the information percolates from the broker used by the informed trader to other market participants, i.e., second-degree information diffusion. We

[1] Recently, Credit Suisse and Citi were accused of leaking information about customer orders to other market participants (see, for instance, Liz Moyer, "Regulators aren't done with 'Dark Pool' investigation," *New York Times*, February 1 2016.)

[2] Furthermore, network centrality goes above and beyond capturing the size of the broker, as measured by the volume that it intermediates. In fact, we control for the total volume of the trades intermediated by each broker without affecting our findings. We also show that differences in trade execution quality between central and peripheral brokers cannot explain our results.

[3] Relatedly, Farboodi and Veldkamp (2017) provide a long-run growth model where traders have the option to extract information from order-flow data mining, and study the implication for price informativeness and market liquidity.

do so by looking at how the distance between brokers (nodes in the network) affects the traders' access to the information. Moving one node away from the broker that executes the informed trade reduces the probability of taking advantage of this information by 25%, which provides an estimate of how information diffusion decays through the network.

We provide results that are inconsistent with several alternative explanations. Brokers do not seem to produce the information, but rather they acquire it from their informed clients. Originator and followers do not trade in a correlated fashion because they follow similar styles (Barberis and Shleifer, 2003), because they react to the same information, or because the managers independently communicate with each other. Furthermore, we provide evidence suggesting that the information shared by the broker is not exclusively about order flow, but rather it allows other market participants to take advantage of information about fundamentals.

The previous results centered on the idea that information is generated by unusually large trades and then percolates through the brokers to other investors. Another natural setting in which we test the information hypothesis is activist stake buildups. In fact, activists have to file a 13D form with the Securities and Exchange Commission (SEC) within ten days of reaching a 5% stake in the company they are targeting. Existing works have shown that most of the trades are clustered right around this 5% threshold (see, among others, Brav et al., 2008; Collin-Dufresne and Fos, 2015). Furthermore, activists do not have an incentive to release their intent before they build up their positions, as that would create unwanted competition from other traders.[4] In other words, before the 13D filing, it is likely that only the broker employed to execute the activist's trades has information about the activist purchases. Then, if brokers were releasing information about their incoming orders, we should expect other traders to buy the stock of the target company before the 13D filing.

To test this hypothesis, we collect information about the dates and targets from the 13D forms as well as the broker employed by the activist. We show that other clients of this broker are significantly more likely to buy the stock of the activist's target firm right before the 13D filing, which confirms our information hypothesis.

Overall, the previous results shed light on the source of the advantage for central brokers in generating excess returns by highlighting that they tend to disseminate the information gathered from informed traders. These results raise the question of why an informed asset manager should be willing to give up part of its informational advantage by trading with brokers that tend to leak to other market participants. One potential answer relies on the repeated nature of the trading relationship between broker and asset manager. Specifically, we find that being an informed trader in the past predicts being a follower in the future. This suggests that some asset managers are willing to give up some of their informational advantage to receive rents when other market participants are informed. Accordingly, we show that the net present value (NPV) of executing the informed trades through the same broker is positive. Although when informed, asset managers face higher price impact due to information leakage when they are uninformed, traders earn excess returns by acting on the leaked information that more than compensate them. Importantly, the returns from trading on leaked information are about twice as large as the normal trading performance of a manager, and they provide around 26% of the trading profits in the month in which they occur.

Finally, we investigate the price formation process and gage the importance of broker information leakage for price discovery. We find that when large informed trades are intermediated by central brokers, which are more likely to leak the information, the price converges to its new long-run level 50% faster. Additionally, we study how the release of private information during the activist stake buildup period contributes to price discovery. We assume that when the clients of the activist's broker are significant buyers of the target stock before the release of public information (i.e., the prior to the filing of the 13D form), they are beneficiaries of information leaks. In these cases, about 4% out of 5.19% cumulative returns over the [−10,25] window around 13D filings is realized in the ten days before the filing. Thus, information leakage seems to be an important contributor to price discovery in the settings that we consider.

Overall, our findings indicate that, although we are analyzing an exchange where prices are public information, and not an over-the-counter (OTC) market, intermediaries play a key role in the acquisition and dissemination of private information, which they extract from their clients' order flow.

Several other recent papers have reexamined the way in which information spreads in financial markets. For instance, Babus and Kondor (2016) have focused on information aggregation when agents trade in a network setting, such as OTC markets. Yang and Zhu (2016) provide a two-period Kyle (1985) model of back-running, where, in addition to informed and noise traders, there is an investor who learns from the order flow generated by the informed speculator after the order is filled. Although we analyze data from the stock market, which is a centralized market, these studies provide a fitting background for the empirical work in this paper. In fact, our results provide evidence for the theoretical insights in Babus and Kondor (2016) that central broker-dealers are able to learn more than peripheral ones and confirm the idea presented in Yang and Zhu (2016) that traders might back-run informed

4 In some circumstances, activist investors may communicate their stake buildup to other activist investors to carry out a coordinated action toward the target company (wolf-pack agreements). However, the wolf-pack agreements involve a group of activist investors. In our trading data (Ancerno), there are no activists. We identify the activism events using 13D files and the activists' brokers using the Uniform Application for Investment Adviser Registration and Report by Exempt Reporting Adviser (ADV) files and hedge fund databases. Hence, the institutions in Ancerno that imitate the activists cannot be activists, and therefore they are unlikely to be part of a wolf pack. Furthermore, due to SEC regulations, activists are required to disclose if they worked in coordination with other market participants on their campaign (Section 13(d) of the Securities Exchange Act of 1934). We verified that no such case occurred in the events under consideration.

traders by observing the order-flow, which provides a way for the information to spread in the market.

Our findings also relate to the papers studying information percolation in financial markets, such as Duffie et al. (2009, 2014), Duffie et al. (2010), and especially Andrei and Cujean (2017), who show how information percolation might lead to momentum and reversals.[5] The common feature of these models is that agents exchange information in random, bilateral private meetings but trade in centralized markets. Our paper shows that information percolation might not be driven by random meetings between traders, but rather be conveyed by brokers who gather the information through their trade intermediation and then disseminate it to their clients.[6]

Lately, the study of trading networks has made some forays into the empirical finance literature as well. The recent paper by Di Maggio et al. (2017) studies the network of dealers in the corporate bond market.[7] The authors show that dealers provide liquidity in periods of distress to the counterparties with which they have the strongest ties. However, the paper also gives evidence of the inherent fragility of the network structure as the failure of a core dealer causes the connected dealers to change their pricing functions and to become less profitable.[8,9] All of the existing evidence is for OTC markets, while we analyze the United States stock market and provide evidence of the information-diffusion mechanism through which the network of broker–investors relationships affects returns.

A complementary approach to studying how information is shared in the market has recently been proposed by Boyarchenko et al. (2016), who build a model and calibrate it to the Treasury auction data.[10] They use this model to quantify counterfactuals about policy intervention that would ban information sharing between dealers and with clients.[11]

The remainder of the paper is organized as follows. Section 2 develops the main testable hypotheses, and Section 3 describes the data sources and summary statistics. Section 4 reports the motivating evidence that trading through more central brokers leads to higher abnormal returns. Section 5 presents evidence that central brokers collect and disseminate information, allowing investors to generate superior returns. Section 6 studies the stability of broker and managers behavior in a cooperative equilibrium. Section 7 presents the implications for price behavior and price discovery, while Section 8 concludes.

2. Hypotheses development

This section provides a discussion of the theoretical background that motivates our empirical analysis. Specifically, we formulate the testable hypotheses that we bring to the data. Moreover, we contrast these conjectures to alternative hypotheses that could also have empirical relevance.

Some recent theoretical work posits that the network of trading relations among market participants has implications for information diffusion in financial markets. Specifically, Babus and Kondor (2016) propose a network model of trade in OTC markets where dealers trade privately informed investors. The main result is that central dealers tend to learn more, trade more at lower costs, and earn higher expected profit.

Babus and Kondor (2016) frame their result in the context of OTC markets, but the intuition that central players have an advantage to learn from the orders they observe and execute carries over to a centralized market such as the equity market. In the stock market, brokers intermediate the trades of informed and uninformed clients. Due to the repeated nature of this interaction, brokers can infer the type of the investor whose trade they execute. Hence, they can extract private information from the order flow that they observe. Analogously to central dealers in OTC markets, central brokers aggregate more information flows. Then, if central brokers pass along the information to their clients, and the clients execute the orders with the same broker, we should observe that trades executed through central brokers are more profitable. This argument leads us to the following testable hypothesis:

Hypothesis 1. The trades executed by central brokers are more profitable than those executed by peripheral brokers.

We can then explore the conjectured mechanism in more detail by focusing on its implications for order flow. In particular, one natural way in which brokers can profit from extracting and spreading information is by attracting

[5] Also related is Walden (2014), who shows that agents who are more closely connected have similar trades in the context of a dynamic noisy rational expectations model.

[6] Our paper is more distantly related to models of learning in arbitrarily connected social networks (see for instance, Acemoglu et al., 2011; Bala and Goyal 1998, Colla and Mele 2010, DeMarzo et al., 2003, and Golub and Jackson 2010) and the papers providing evidence that the network structure influences information aggregation in the context of aid programs (Alatas et al., 2016), technology adoption (Bandiera, and Rasul, 2006; Duflo et al., 2004; and Conley and Udry 2010) or microfinance, and public health (e.g., Munshi, 2003; Bandiera, et al., 2009; Banerjee et al., 2013; Kremer and Miguel, 2007).

[7] Other recent papers have studied the role of the network in different markets (see, for instance, Hochberg et al., 2007; Li and Schürhoff, 2014; Hollifield et al., 2014; Afonso et al., 2013; Hendershott et al., 2016).

[8] A related work is Gabrieli and Georg (2014), which studies liquidity reallocation in the European interbank.

[9] Another strand of finance literature that uses concepts drawn from network analysis is concerned with the effect of social networks on different measures of financial behavior (see Cohen et al., 2010; Fracassi and Tate, 2012; Shue, 2013; Lerner and Malmendier, 2013; Nguyen, 2012).

[10] The hypothesis that financial intermediaries share order-flow information is supported by Hortacsu and Kastl (2012). They use data from Canadian Treasury auctions to show that dealers learn and share order flow information, and that it also accounts for an important fraction of dealers' surplus. Barbon et al. (2017) show that brokers can also leak information about order flow and foster predatory trading by their other clients during "fire sales."

[11] Also related are the papers studying how cooperation and reputation among intermediaries affect liquidity costs in exchange markets. Battalio et al. (2007) show an increase in liquidity costs in the trading days surrounding a stock's relocation to the floor of the exchange, while Pagano and Röell, (1996) and Benveniste et al. (1992) demonstrate that reputation attenuate the repercussions of information asymmetries in trading and liquidity provision.

higher trading volume. To this purpose, brokers can leak information to their clients in the expectation that these clients will use the information to place trades with the same broker in a quid pro quo.[12] Given that the private information may be short lived, these trades should be executed right after the broker obtains and spreads the information. Hence, we should find commonality in the order flow that passes through a broker, right after the broker executes an informed trade. This argument suggests the following testable hypothesis:

Hypothesis 2. Following an informed trade, the order flow that passes through the broker that executes the trade is more likely to be in the same direction as the informed trade. Moreover, this effect should be stronger through central brokers because they are more likely to detect informed trades.

We note that, because the imitation of the informed trade is likely to occur soon after the broker extracts the private information, there is potentially a negative externality from the followers of the informed trade to the originator of this trade. In particular, if the originator is still building (or unwinding in the case of sales) the position, the followers' and the originator's trades compete for the same asset in the same direction, raising the trading costs for the informed trader. Yang and Zhu (2016) propose a two-period Kyle (1985) model where an uninformed trader learns from past order flow, allowing the uninformed trader to compete with the informed investor. The interaction described in *H2* is therefore consistent with their model.

Furthermore, in *H2*, we conjecture that central brokers are more likely to spread the information than peripheral ones. Arguably, central brokers are in the business of dealing with private information. In a sense, their business model partly relies on the extraction of information from, and the provision of information to, their clients. Consequently, central brokers attract clients that are more likely to take advantage of information (e.g., active funds) and are in the position to do so. Also important, because central brokers observe more order flow than peripheral brokers, they are also better at separating informed from uninformed trades when they see them.

The rents extracted by the broker can quickly dissipate if too many investors trade on the same information. Hence, to preserve the value of this information, brokers have an incentive to pass the information to the investors with whom the quid pro quo is more likely to occur, i.e., the broker's best clients. Hence, we expect heterogeneity among the clients of the same broker. In particular,

Hypothesis 3. The clients exhibiting the strongest trading relationship with the broker should be the ones benefiting the most from the information leakage.

Intuitively, the first to receive the tip from the broker should be the ones that are more likely to respond by trading on that information with the same broker. There is recent evidence in the literature that, indeed, the strength of relations among market participants affects trading outcomes (e.g., Di Maggio et al., 2017).

The evidence that is consistent with Hypotheses 1-3 could result from alternative explanations. For instance, the commonality of trades that would be consistent with Hypothesis 2 (H2) may instead be the consequence of public information to which all managers react, in a manifestation of the reflection problem (Manski, 1993). A somewhat different declination of this alternative hypothesis is that commonality of trades is due to the fact that the managers trading with the same broker follow similar trading strategies. These considerations suggest the following alternative hypothesis:

Alternative Hypothesis 1. Asset managers exhibit commonality in trading because they respond to public news or because they follow similar trading strategies.

To separate H2 from Alternative Hypothesis 1 (AH1), we need to develop tests that condition on specific information sets of either the brokers or the followers of the informed trades. For instance, we can exclude from our sample stocks and days where public news is released, e.g., days around earning announcements or analyst recommendations. Moreover, we can investigate whether the commonality between asset managers' trades is specific to the broker through which the informed trade is executed. That is, if the broker extracts and passes along the information, then the correlated order flow should be concentrated with this broker. Instead, if managers react to public news, the commonality in order flow should also appear in trades with other brokers. Additionally, we can focus on events in which the originator's trades are clearly the outcome of private information and test whether commonality is present there too, an example of these events are the buildup of activist stakes.

A distinct explanation that is partly observationally equivalent to H1–H3 is that brokers are the original source of fundamental information. Specifically, the brokers' research departments may produce original research on a company, which they then pass to investors as part of brokerage services. This conjecture leads to

Alternative Hypothesis 2. The broker's research department produces the information, which is then disseminated to the broker's clients.

To rule out Alternative Hypothesis 2 (AH2), we can exclude all the stocks that are followed by the broker's research department, using information on earnings forecasts and analysts' recommendations, and test whether evidence of commonality in order flow is also present in this subsample.

At this point, a natural question concerns the stability of an equilibrium in which informed traders stick with brokers that extract and reveal their private information. Informed investors can in principle redirect their trades to brokers that do not leak information. In other words, after

[12] Recently, brokers and other intermediaries have also generated profits by directly selling information about the order flow to institutional investors. For example, NASDAQ is seeking the SEC's approval for an options-data service called the "Intellicator Analytic Tool." This new service would provide market color to subscribers by revealing whether a trade was initiated by a small investor or a big money manager (see Alexander Osipovich, "Wall Street fears Nasdaq proposal would expose trading secrets," *Wall Street Journal*, November 9 2017).

observing the information leakage, informed traders could punish the broker and terminate the relationship. In turn, anticipating this punishment, brokers abstain from misbehaving. To address the sustainability in equilibrium of brokers' information leakage, we conjecture a repeated interaction in which clients and brokers decide to cooperate. In particular, informed clients find it beneficial to give up part of their informational rents to obtain private information from other clients of the broker in other iterations of this game. Thus, we formulate

Hypothesis 4. The club hypothesis: informed traders find it profitable to direct their trades to a leaking broker because the loss due to the information leakage is more than compensated by the gains derived from trading on the information generated by the other clients of the broker in different trading rounds.

The results of the tests of Hypothesis (HV) could prove to be of great value to the theoretical literature if they showed evidence of long-term relations between brokers and asset managers. In particular, the existing literature does not consider the key fact that the interactions between brokers and asset managers are repeated over time. While it may be optimal to hide informed trades from a leaking broker in a one-shot game, this conclusion may be reversed in a dynamic interaction, where the same informed trader benefits from learning about others' information. Furthermore, the broker acts as a monitoring and enforcing device by making sure that the asset managers do not defect by submitting their informed orders to different brokers. To test H4, we can then study whether being an informed trader with a specific broker results in a higher likelihood of receiving information from the same broker in the future.

The analysis in Yang and Zhu (2016) also suggests that information leakage is likely to have implications for price discovery. For instance, prices could reach the new fundamental level faster because of competition between informed and uninformed investors. Thus, if brokers extract and disseminate private information to uninformed investors, who then imitate the informed trade, it follows that brokers' leakage improves price discovery. These considerations lead to the following prediction

Hypothesis 5. Prices converge faster to fundamentals when central brokers intermediate informed trades than when peripheral brokers do.

We can test this hypothesis by comparing the price reaction to informational-relevant events when information leakage occurs and when it does not, which is helpful in quantifying the importance of our information leakage mechanism for price discovery.

3. Data and summary statistics

To analyze whether and how the broker network shapes trading outcomes and information diffusion in the market, one needs a detailed trade-level data set that also reports information on the institutional investors and brokers involved in each trade. Abel Noser Solutions, formerly Ancerno Ltd. (we retain the name "Ancerno" for simplicity), fittingly provides this information. Ancerno performs transaction cost analysis for institutional investors and makes these data available for academic research with a delay of three quarters under the agreement of non-disclosure of institutional identity.

We have access to anonymous identifiers for managers that initiate the trades and brokers that intermediate those trades from 1999 to 2014.[13] There are several advantages to this data set. First, clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggesting that the data should not suffer from self-reporting bias. Second, Ancerno is free of survivorship biases, as it includes information about institutions that were reporting in the past but at some point terminated their relationship with Ancerno. Finally, the data set is devoid of backfill bias, as Ancerno reports only the trades that are dated from the start of the client relationship. Previous studies, such as Puckett and Yan (2011) and Anand et al. (2012, 2013), have shown that the characteristics of stocks traded and held by Ancerno institutions and the return performance of the trades are comparable to those in 13F mandatory filings.

Ancerno information is organized on different layers. 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 Committee on Uniform Security Identification Procedures number (CUSIP). We also know whether the trades are part of a unique ticket (i.e., an order with a broker). Our analysis is carried out at the ticket level. We therefore aggregate all trades belonging to the same order, by the same manager, executed through the same broker, on the same day.

Since the network of brokers generates our main source of variation, we provide several summary statistics to describe it. To limit noise in the definition of the broker network, we focus on the trades executed through the top 30 brokers by volume in the prior six months.[14] These brokers intermediate more than 80% of the whole volume in the data set.

Fig. 1 depicts the network in this market. The larger blue circles represent the brokers in the market, the size of the circle being proportional to broker centrality. The smaller nodes capture the investors, with darker dots representing investors trading larger volumes. The brokers are connected to each other only through the investors. The investors in the periphery are the ones that are connected with only one or two brokers. The average broker has more than 110 fund managers as clients. Fig. 2 plots the distribution of the number of brokers per manager. The average manager uses about eight brokers to execute its trades. However, Fig. 3 shows that the asset managers have very strong relationships with specific brokers. In fact, more than 40% of the trades are concentrated with just the top

[13] Relative to the standard release of Ancerno that is available to other researchers, we managed to obtain numerical manager and broker identifiers also for the latest years (that is, after 2011) under the agreement that we will not try to identify institutional names.

[14] We have an agreement with our data provider that prevents us from disclosing the broker and trader identities.

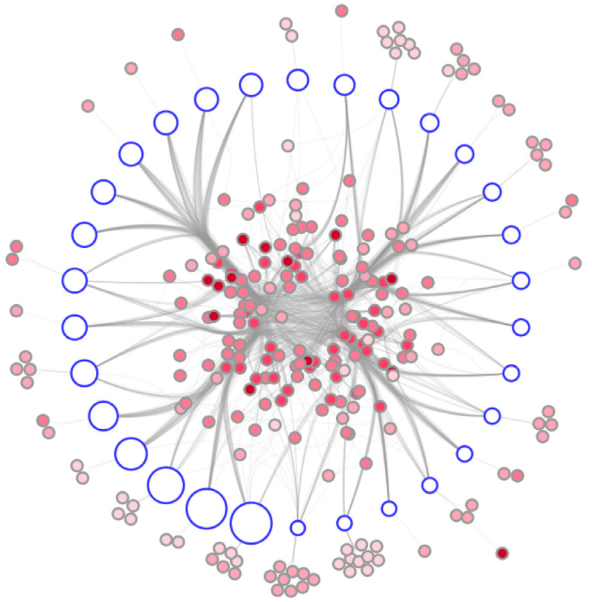

Fig. 1. This figure depicts the network of managers (gray circles) and brokers (blue circles). The brokers are artificially set to stand in circle; their position and size depends on their measure of eigenvector centrality at the time in which the network was estimated. The managers outside of the broker circle interact only with one or two brokers in the period, the others stand in the middle, acting as a link between a broker and the others. The colors of the managers' circles depend on the dollar volume traded by the manager in the period: from a low volume (in pale pink-or a light gray) up to a very high volume (in intense red-or an intense gray). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

broker, while more than 80% are executed by the top five brokers for the average manager.

Our setting would suggest a measure of degree centrality weighted by the performance of the managers. Indeed, we wish to capture access to information by the more informed brokers, that is, those that tend to execute the trades of the smart money (i.e. the managers with better

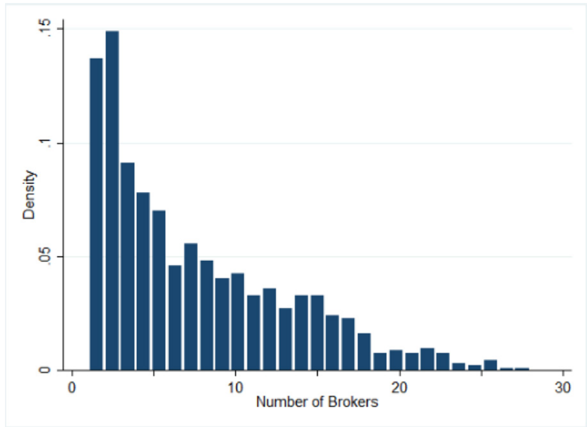

Fig. 2. This figure plots the histogram of the average number of brokers used by the asset managers in our sample.

performance). However, the trading performance of the asset managers itself depends on centrality. This is the main testable hypothesis of the paper. Thus, if we used performance weights, we would find a mechanical relation between centrality and performance.

On the other hand, eigenvector centrality does not depend for its construction on performance, while capturing an important feature of the data: smart money managers in this market are more likely to use multiple brokers, and as a result, they end up being more central. In turn, central brokers will have access to better information through their interaction with central managers. This is our motivation for using centrality.

Therefore, our main measure of broker centrality is eigenvector centrality (Bonacich, 1972, 1987; Katz, 1953; and Bonacich and Lloyd, 2001) and provide robustness analysis using other definitions. This variable takes into account all direct and indirect trading partners of a given broker (i.e., fund managers and other brokers) and is computed by assigning scores to all brokers and managers in the bipartite network of trading relations. A

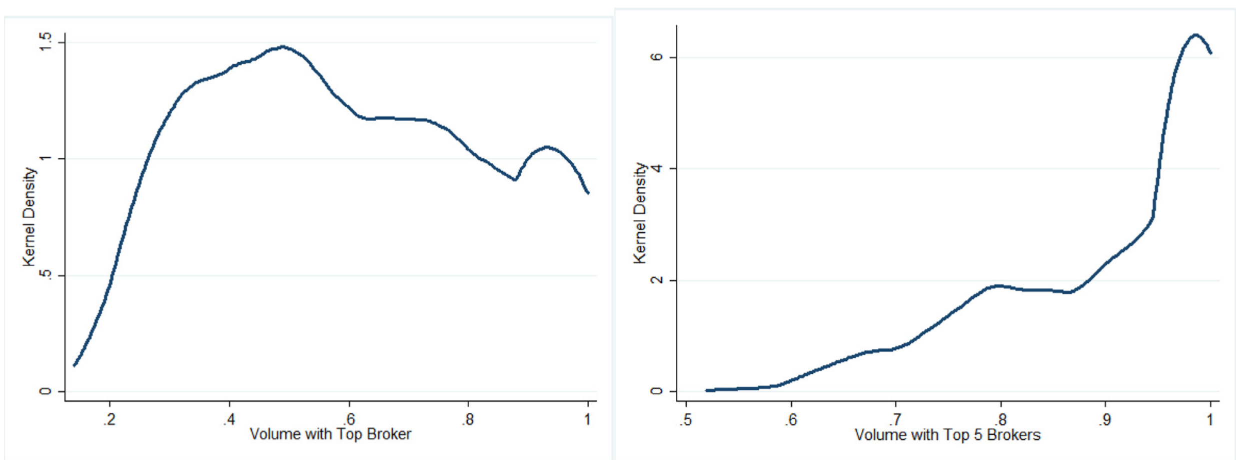

Fig. 3. This figure plots the kernel density for the average fraction of trades intermediated by the top broker (left panel) and by the top five brokers (right panel).

Table 1
Summary statistics.
This table reports the summary statistics at different level of aggregation of the data. Panel A reports the main summary statistics for the brokers. Panel B differentiates between central and peripheral brokers and reports the difference. Panel C also reports the differences between brokers that intermediate volume above and below the median. Panel D reports statistics for the stocks traded through central and peripheral brokers. Panel E reports the average eigenvector centrality for different classes of managers. Panel F reports statistics about the fraction of trades that are split across brokers. For each manager, we compute a volume-weighted average of the eigenvector centrality of the brokers chosen by the manager to execute their trades. Then, in each month, we rank the managers based on their characteristics and compute the average centrality of the brokers used by managers who lie above or below the cross-sectional median of the characteristic of interest. The characteristics we take into consideration are proxies of the managers' turnover (churn ratio and adjusted churn ratio), size (net volume and total volume), information (past performance and hedge fund), and degree of activeness (active and adj. active). A manager's Churn ratio is their net trades over their gross trades. The Adjusted churn ratio is this figure adjusted by the number of times a manager's net trades changes sign within a quarter. Net volume is a manager's buy volume less his sell volume, and Total volume is the total dollar volume traded; both measures are computed over the previous six months. Past performance is the manager's performance on trades made within the six previous months, where the return on each trade is estimated at the end of the month of the trade. Hedge fund is a categorical variable that specifies whether or not a manager is a hedge fund. Active is the ratio of manager's trading activity (measured in dollar volume traded) to the dollar volume traded over the previous six months. Adjusted active is computed similarly but standardizes the volume traded on each stock by the stock's market capitalization. Asterisks denote significance levels (*** = 1%, ** = 5%, * = 10%).

Panel A: All brokers

	All brokers					
Variable	Average	StdDev	P25	Median	P75	Obs
Eig. Centrality	0.1067	0.0725	0.0540	0.0985	0.1337	5569
Cumul. Volume (% Ancerno)	82.66%	1.44%	81.43%	82.66%	83.38%	5569
Price Impact (bps)	10.52	12.52	3.87	9.37	16.02	5568
Trading Fees (cents)	2.87	1.15	1.95	2.57	3.65	5477
Trading Fees (bps)	11.96	11.96	11.96	11.96	11.96	5477
Trading Time (seconds)	16,321	4189	13,614	16,239	19,442	5569
Volume Per Trade (usd)	3,72,120	2,21,241	2,33,544	3,12,321	4,50,588	5569

Panel B: Central vs. peripheral crokers

	Centrality below median		Centrality above median		Centrality vs peripheral
Variable	Average	StdDev	Average	StdDev	0.0995 ***
Eig. centrality	0.057	0.0296	0.1565	0.0685	1.33%***
Volume (% Ancerno)	0.021	0.02	0.0343	0.0241	1.03***
Price impact (bps)	10.01	11.54	11.04	13.41	−0.24***
Trading fees (cents)	2.98	1.09	2.75	1.19	−0.94***
Trading fees (bps)	12.42	4.8	11.48	5.33	−56
Trading time (seconds)	16,349	4358	16,293	4014	41,959***
Volume per trade (usd)	351,159	181,904	393,118	252,925	0.0995***

Panel C: High vs. low volume

	Volume below median		Volume above median		High vs. low volume
Variable	Average	StdDev	Average	StdDev	0.0097***
Eig. Centrality	0.1018	0.0811	0.1115	0.0624	3.59%***
Volume (% Ancerno)	0.96%	0.32%	4.55%	2.03%	−2.17***
Price impact (bps)	11.61	14.47	9.44	10.11	−0.57***
Trading fees (cents)	3.16	1.20	2.58	1.01	−2.31***
Trading fees (bps)	13.12	5.27	10.81	4.62	592***
Trading time (seconds)	16,024	4728	16,617	3549	−87,178***
Volume per trade (usd)	4,15,795	2,57,786	3,28,617	1,66,536	0.0097***

Panel D: Stocks

	Stocks traded by central brokers		Stocks traded by peripheral brokers		Central vs peripheral	
Variable	Average	StdDev	Average	StdDev	Obs	Difference
Market cap.	16.78	34.59	16.02	33.49	2,25,00,187	−0.76***
Amihud past 12m	0.00013	0.00622	0.00014	0.00659	2,24,98,168	9.196E−06***
Amihud	0.00008	0.01128	0.00010	0.01277	2,26,90,587	1.745E−05***
Analyst coverage	13.36	8.08	13.30	8.15	2,04,86,038	−0.06***
Std. dev. of analyst est.	7.85%	16.58%	8.28%	17.24%	2,00,34,710	0.43%***

Panel E: Broker choice by different classes of managers

Average eigenvector centrality of the brokers chosen by different classes of managers

Manager classification	Low	High	Difference	t-stat	*p*-value
Churn ratio	0.0870	0.0934	0.0065	21.98***	0.000
Adj. churn ratio	0.0867	0.0937	0.0069	23.54***	0.000

(*continued on next page*)

Table 1
(*continued*)

Net volume	0.0862	0.0943	0.0081	28.06 ***	0.000
Total volume	0.0857	0.0947	0.0090	31.38***	0.000
Past performance	0.0897	0.0907	0.0010	3.48***	0.000
Hedge fund (no/yes)	0.0901	0.0908	0.0008	2.27 **	0.023
Active	0.0896	0.0909	0.0014	4.68***	0.000
Adj. active	0.0896	0.0909	0.0013	4.60***	0.000

Panel F. Trades split across brokers

	N	mean	sd	p10	p25	p50	p75	p90
				Share of volume				
Top broker	69,360	0.516	0.285	0.196	0.274	0.438	0.735	1
Top three brokers	69,360	0.777	0.210	0.468	0.596	0.811	1	1
Top five brokers	69,360	0.878	0.146	0.646	0.774	0.948	1	1
				Share of trades				
Top broker	69,360	0.442	0.319	0.092	0.173	0.345	0.667	1
Top three brokers	69,360	0.707	0.264	0.332	0.482	0.733	1	1
Top five brokers	69,360	0.824	0.200	0.519	0.679	0.900	1	1
				Trade split between brokers				
One broker	69,360	0.833	0.218	0.504	0.725	0.935	1	1
Two brokers	69,360	0.119	0.157	0	0	0.053	0.200	0.323
Three brokers	69,360	0.030	0.074	0	0	0	0.023	0.107
Four or more brokers	69,360	0.017	0.068	0	0	0	0	0.037

broker–manager connection is weighted by the fraction of the total volume of the broker that is executed with the manager, where the volumes are computed over the prior six months. A broker's connection to managers that, in turn, are connected to many other brokers increases the broker's centrality score more than a similar number of connections to managers that only trade with that broker. In other words, what counts is not only the number of connections of a broker but also who the broker is connected to. Fig. A.1 in the Internet Appendix shows the kernel density estimation of the centrality measure. It shows that there is significant variation across brokers and that the distribution of the centrality measure is positively skewed, with the mass of brokers having low values and very few exhibiting very large values.

Central brokers can differ along other dimensions from the peripheral ones; for instance, they might charge different fees or have different price impact and execution speeds. Table 1 presents the summary statistics with Panel A and B focusing on the broker characteristics. We report the average of these characteristics for the top and bottom brokers in terms of their centrality. We find that top brokers intermediate higher volume, about 1% difference, have, on average, higher price impact, charge lower fees, display similar trade execution time, and intermediate higher volumes per trade.

We also ask whether the centrality measure is just identifying the largest brokers. To verify this, we rank brokers based on the total volume they intermediate in each month and find that there is only an 8% correlation between the network centrality measure and the volume ranking. Furthermore, in the next section, we provide evidence that our results remain unaffected when we control for the volume intermediated by the broker. Fig. A.2 reports the coefficients of a regression of the centrality measure on its lags. It shows that our centrality measure is very persistent. Panel C of Table 1 complements the previous statistics by comparing brokers that intermediate volumes above and below the median. It shows that the differences in price impact and trading fees are even more significant: larger brokers have about 20% lower price impact and fees.

About 3000 stocks are traded over our sample period by about 360 managers and 30 brokers (which is the number of brokers that we decided to focus on, see above). Panel D of Table 1 complements the previous evidence by providing key statistics for the stocks traded by different brokers. We find that central brokers tend to trade stocks that have lower market capitalization, are more illiquid, as captured by higher Amihud (2002) illiquidity measure, and exhibit lower analyst coverage and higher standard deviation of the analysts' estimates. These statistics suggest a greater role for information acquired by observing order flow. This information is more valuable when the stock is illiquid and when there is less public information (lower analyst coverage) or nosier information (higher dispersion of analysts' estimates). The key advantage of our empirical methodology is the possibility to control for these differences, for instance, by comparing similar trades for the same stock initiated by the same manager within the same timeframe.

To show that the centrality measure is a good proxy for the brokers' access to information, Panel E of Table 1 reports the characteristics of the managers trading with central and peripheral brokers. First, we measure the managers' horizon by computing their churn ratio and show that managers with shorter horizon are more likely to use central brokers to execute their trades. We also find that the managers that generate a higher total and net volume trade prevalently with central brokers. Furthermore, funds with higher past trading performance also tend to trade more with central brokers. Finally, we identify the hedge funds in the database, as well as distinguish managers between active and passive, and show that hedge funds and more active asset managers are more likely to trade with central brokers.

Furthermore, we can quantify the persistence in manager–broker relationships. More specifically, for each month, we rank each manager's broker by total dollar volume intermediated. Then, we estimate the transition probability matrix that a broker remains a manager's top broker from month t to $t+1$. We find high persistence in the relation. A broker remains in top spot with probability 47.1%, and in the top three 75% of the time, suggesting that there is high persistence in the manager–broker relationship.

Panel F reports the share of trading activity with the top broker, the top three brokers, and the top five brokers. The results displayed below are estimated at the manager-month frequency. We see that 51.6% of a manager's volume is intermediated with the top broker, compared with 77.7% with the top three brokers, and 87.8% with the top five. We also examine how much volume is coming from trades spread across multiple brokers. We aggregate trades on a stock by a manager made at the same time (within the same day) across one or multiple brokers. We find that, on average, 83.3% of a manager's volume is executed with one brokers, compared with 11.9% with two brokers and just 3% and 1.7% with three brokers and four or more brokers, respectively.

Finally, we can more formally test the idea that central brokers are more likely to be used for informed trades that require fast execution, when information can lose value quickly, while investors who wish to trade for liquidity purposes choose peripheral brokers. For example, index funds scaling their portfolios up and down in response to flows would go to a peripheral broker to have their order worked slowly and at lower risk of front running.

To test this conjecture further, we use a standard measure of trade informativeness in the microstructure literature, i.e., the permanent component of price impact (Collin-Dufresne and Fos, 2015; van Kervel and Menkveld, 2017). This measure is computed by taking the difference between the price level after trade completion and the price level before trade initiation. In particular, we use the opening price on the stock on the first trading date of the order as pre trade price. The post-trade price measures are either the execution price of the final child trade on the order or the closing price one trading day after the final day.

In Table 2, we regress the price impact measure on an indicator equal to one if the broker intermediating the order is above median centrality for that month and the log dollar volume of the order. Columns 1–4 display the results with the dependent variable as permanent price impact measured from open to final execution price, and Columns 5–8 show the results with permanent price impact measured from open to close one day after the final trading day. In Columns 1–2 and 5–6, we focus on the entire sample of manager–broker-stock-order observations, whereas in Columns 3–4 and 7–8, we focus on orders with more than one child trade. Intuitively, multiple trades in the same stock are more likely to be driven by information. Columns 1, 3, 5, and 7 include manager, stock, and day fixed effects; Columns 2, 4, 6, and 8 include stock-week and manager fixed effects. *T*-statistics based on robust standard errors, double clustered at the week and stock level, are reported in parentheses.

Overall, we find supporting evidence for the view that investors tend to route their informed orders through central brokers since the price impact of the orders executed by central brokers is higher both for the overall sample and even more so for the subset of multiple trades. Peripheral brokers are more likely to intermediate orders with less informational content.

4. Motivating evidence: network centrality and trading profitability

In this section, we provide evidence that central brokers are associated with significantly positive abnormal returns in both a portfolio setting and in regressions at the trade level supporting H1. We take this evidence as a motivation for the later analysis searching for a role of brokers in spreading private information.

4.1. Portfolio analysis

We start our analysis by constructing monthly portfolios based on broker centrality. The goal is to test whether trades that are intermediated by brokers that are more central involve better performing stocks. One advantage of this methodology is the ability to report the economic significance of broker centrality for investors in a transparent way. This approach, however, is not immune to the concern that centrality correlates with some underlying stock characteristic that, in turn, correlates with expected returns. We address this concern in later analysis.

In detail, every three months, for each broker, we assign to each stock a score from one to ten based on the signed volume intermediated by the broker in that stock: a score of one indicates a heavily sold stocks (through the broker), and a score of ten indicates a heavily bought stocks. If a stock is not traded by any broker in the quarter, then we remove it from our set for that quarter. Then we select the top and bottom six brokers (i.e., the top/bottom quintiles) based on our centrality measure, creating in this way two groups: the central and peripheral broker groups. Within each broker group, we compute the group-level stock score as the average of the broker-level stock scores across all the brokers in the group. Finally, for both brokers groups we compute a long/short, value-weighted portfolio buying the stocks with a high group-level score and selling the stocks with a low group-level score. Our final high-minus-low centrality portfolio is built by buying the long/short portfolio of the central brokers and selling the long/short portfolio of the peripheral brokers. A stock remains in the portfolio for three months.[15]

We compute the average monthly returns on the high-minus-low centrality portfolio and obtain alphas from regressions on common risk factors. Panel A of Table 3 reports these results. We provide four specifications: raw returns and alphas from one-factor, three-factor (Fama and French, 1993), and four-factor models (Carhart, 1997). Across specifications, we find a positive and significant per-

[15] We have experimented with other holding periods (one month and six months) and found qualitatively similar results.

Table 2
Price impact.
This table relates price impact of orders and the centrality of the broker. As in Menkveld and Van Kervel (2017), we string child trades together into meta orders at the manager–broker-stock-order level. First, for each manager–broker-stock-day, all child orders are aggregated together. Then, as in Korajczyk and Murphy (2018), orders are strung across days if the last child trade on trading date s occurs in the last half hour and the first child trade on trading date $s+1$ occurs in the first half hour. Price impact at the manager-broker-stock-order level is computed as follows:

$$PriceImpact = q[\ln(p^{end}) - \ln(p^{start})] \times 10,000,$$

where q is equal to 1 for buy orders and −1 for sell orders, thus converting sells into pseudo-buys. The starting price measure is the opening price on the stock on the first trading date of the order. The ending price measures are the execution price of the final child trade on the order and the closing price one trading day after the final day. In each specification, we regress the price impact measure on an indicator equal to one if the broker intermediating the order is above median centrality for that month and the log dollar volume of the order. Columns 1–4 display the results with the dependent variable as price impact from open to final execution price and Columns 5–8 show the results with price impact from open to close one day after the final trading day. In Columns 1–2 and 5–6, we focus on the entire sample of manager–broker-stock-order observations, whereas in Columns 3–4 and 7–8, we focus on orders with more than one child trade. Columns 1, 3, 5, and 7 include manager, stock, and day fixed effects; Columns 2, 4, 6, and 8 include stock-week and manager fixed effects. T-stats based on robust standard errors, double clustered at the week and stock level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price impact sample	Open to final execution				Open to +1 day close			
	All		Multiple trades		All		Multiple trades	
Central broker	1.737***	1.666***	2.551***	2.194***	1.775***	1.692***	3.117***	2.623***
	(6.041)	(5.520)	(7.269)	(5.655)	(3.251)	(2.997)	(4.827)	(3.777)
Log volume	4.469***	4.509***	5.668***	5.502***	3.093***	3.084***	3.564***	3.378***
	(28.761)	(27.686)	(21.411)	(16.469)	(12.088)	(11.663)	(7.890)	(6.398)
Day FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock FE	Yes	No	Yes	No	Yes	No	Yes	No
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-week FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	5,04,84,855	5,00,68,236	1,17,63,631	1,13,59,453	5,04,84,855	5,00,68,236	1,17,63,631	1,13,59,453
R-squared	0.013	0.086	0.032	0.180	0.010	0.096	0.027	0.199

formance for the high-minus-low centrality portfolio. Irrespective of the model, the alpha is around 40 basis points per month, which is about 4.8% on an annual basis. Panel B reports the performance of the two legs of the portfolio, showing that significant excess returns are generated for almost two-thirds by the long leg and for one-third by the short leg. This suggests that the 40 basis points (bps) excess returns are a combination of the trades executed through central brokers performing better than the market and the trades executed by peripheral ones underperforming it. This evidence supports hypothesis H1.

One potential explanation for the observed outperformance of central brokers' stocks is a price pressure effect, similar to that identified by Coval and Stafford (2007). For example, central brokers may intermediate trades by investors that need to accommodate large inflows. In this case, the protracted price pressure could explain the abnormal returns. To investigate this possibility, we assess the persistence of the performance identified by the centrality measure. If the performance reverts toward zero after a few months, a price pressure effect is more likely. Hence, we extend the rebalancing frequency to one year and compute cumulative abnormal returns from a four-factor model. Fig. 4 plots the returns over a 12-month period for this portfolio (circled line). It shows that this high-minus-low centrality portfolio generates excess returns from 0.40% up to 1.2% at longer horizons, significantly better than the close-to-zero returns generated by the portfolio that exploits information about the volume intermediated by all brokers, without conditioning on centrality (crossed line). Then, since the performance is fairly persistent over this horizon, it is unlikely that centrality captures price pressure effects (Coval and Stafford, 2007).

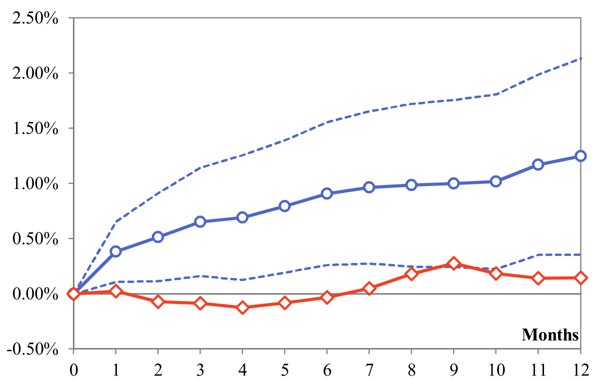

Fig. 4. The figure plots the cumulative return of the high-minus-low centrality portfolio built on month 0 over the following 12 months (without rebalancing every three months), with a 95% confidence interval (in blue-marked by the circles). We also report the cumulative return of a generic long/short portfolio built on month zero (in red-marked by triangles) by conditioning on the imbalances passing through the brokers but without discriminating between central and peripheral brokers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Trade-level results

One concern with the previous results is that the portfolio approach does not allow controlling for heterogeneity at the manager–broker level. For instance, better managers may systematically trade with central brokers. Then, the

Table 3
Portfolio results.
This table reports the estimates of the alpha of the high-minus-low centrality portfolio. We split the brokers in our sample into two categories: central and peripheral. Stocks are ranked every three months based on the average percentage imbalances intermediated by the brokers within each category. For each broker category, we form a value-weighted, long/short portfolio. Both portfolios are long strongly bought stocks and short strongly sold stocks. Our final high-minus-low centrality portfolio is built by buying the central-broker portfolio and selling the peripheral-broker portfolio. Panel A reports the monthly returns of the high-minus-low centrality portfolio regressed on common risk factors. Panel B shows the monthly returns of the long and the short leg of the high-minus-low centrality portfolio (i.e., the central-brokers portfolio and selling the peripheral-brokers portfolio) regressed on common risk factors. *T*-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: High-minus-low centrality portfolio

	Dependent variable: monthly returns of the high-minus-low centrality portfolio			
	(1)	(2)	(3)	(4)
Alpha	46.93***	47.84***	40.88***	42.77***
	(3.169)	(3.212)	(2.762)	(2.890)
Excess market return		−0.0213	−0.0420	−0.0633*
		−0.657	(−1.275)	(−1.774)
SMB			0.135***	0.150***
			(2.934)	(3.199)
HML			0.0543	0.0410
			(1.241)	(0.922)
UMD				−0.0426
				(1.520)
Observations	186	186	186	186
R-squared	0.000	0.002	0.051	0.063

Panel B: Long and short leg of the high-minus-low centrality portfolio separately

	Dependent variable: monthly returns of the long and the short leg of the high-minus-low centrality portfolio							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Long leg				Short leg			
Alpha	29.36**	29.16**	22.97**	23.89**	−17.57*	−18.67*	−17.90*	−18.88*
	(2.602)	(2.567)	(2.050)	(2.124)	(1.814)	(1.923)	(1.812)	(1.907)
Excess market return		0.00464	−0.0116	−0.0219		0.0260	0.0304	0.0414*
		(0.188)	(0.465)	(0.807)		(1.227)	(1.382)	(1.734)
SMB			0.112***	0.120***			−0.0229	−0.0307
			(3.219)	(3.350)			(0.744)	(0.976)
HML			0.0588*	0.0523			0.00444	0.0113
			(1.773)	(1.548)			(0.152)	(0.380)
UMD				−0.0206				0.0220
				(0.966)				(1.175)
Observations	186	186	186	186	186	186	186	186
R-squared	0.000	0.000	0.063	0.068	0.000	0.008	0.011	0.019

observed abnormal portfolio returns might just be the result of a matching between better managers and central brokers.

To address this concern, we exploit the depth of our data and compute a given manager's trading performance with a given broker. In detail, we estimate the following specification

$$Trading\ performance_{ijt} = \beta_1 Broker\ centrality_{jt} + X_{jt} + \gamma_t + \theta_i + \varepsilon_{ijt}\ , \quad (1)$$

where the main dependent variable is the manager's trading performance with a given broker in a month, computed as the value-weighted return of the *T*-day-horizon trades executed by manager *i* through broker *j* during month *t*. In particular, the percentage performance of all trades by a manager with a given broker in a month is computed using closing prices over a *T*-day horizon, with sell trades' performance computed as the negative of a buy trade performance.[16] The performance is computed using all the trades executed within each *T*-day horizon at the execution prices. Then, the performance is averaged across all *T*-day horizons within a month using the dollar volume of the trades as weights. Hence, the frequency is monthly.

The main coefficient of interest in Eq. (1) is β_1, which captures the relation between broker centrality and the manager's trading performance. The vector X_{jt} includes controls, such as the volume intermediated by the broker in the previous six months, as well as the average trade size. Given the granularity of our data, we can include time, manager, and manager-time fixed effects. The time unit is the month. Throughout the analysis, in computing standard errors, we take the most conservative approach, double clustering them at both the manager and the time level. This procedure allows for arbitrary correlation across time and across managers. Table 4, Panel A reports the results where we have divided the centrality measure by its standard deviation for ease of interpretation of the magnitudes (returns are expressed in basis points).

[16] The *T*-day horizon starts at the open of each day and ends after *T* days. The new *T*-day horizon starts after the closing of the previous one, without overlap. We value weight the performance of all the trades in the same *T*-day horizon.

Table 4

Returns and brokers' volume.

This table regresses the value-weighted trading performance at different time horizons (in basis points) on our centrality measures. In Panel A, our database is collapsed at the broker/manager/month level; we include as a control the natural logarithm of the dollar trade volume intermediated by each broker in the last six months and the average dollar volume traded by the manager with the broker in the month in which performance is assessed. In Panel B, our database is collapsed at the broker/manager/stock/month level; thus, we are able to add stock, stock/time, and manager/stock/time fixed effects. The centrality measure is standardized to unit variance. We include as a control the natural logarithm of the dollar trade volume intermediated by each broker in the last six months and the average dollar volume traded (in the stock) by the manager with the broker in the month in which performance is assessed. *T*-stats based on robust standard errors, double clustered at the month and the manager level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Manager level

	Dependent variable: value-weighted trading performance								
	(1)	(2) 1 Day	(3)	(4)	(5) 5 Days	(6)	(7)	(8) 10 Days	(9)
Eig. centrality	0.892***	0.614***	0.555***	1.847***	1.359***	1.294***	2.147***	1.434***	1.619***
	(5.936)	(4.182)	(3.924)	(4.833)	(3.520)	(3.372)	(4.100)	(2.706)	(3.016)
Broker volume	−0.173	0.312*	0.648***	0.0446	1.026**	1.641***	0.154	1.370**	2.114***
	(1.024)	(1.938)	(4.054)	(0.0914)	(2.167)	(3.475)	(0.261)	(2.362)	(3.590)
Average trade size	−1.699***	−2.233***	−2.995***	−3.296***	−4.443***	−5.535***	−3.751***	−4.861***	−5.929***
	(11.58)	(15.57)	(17.74)	(10.79)	(13.81)	(14.66)	(8.250)	(9.584)	(11.44)
Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Manager FE	No	Yes	No	No	Yes	No	No	Yes	No
Manager-Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	6,33,603	6,33,591	6,24,101	6,29,936	6,29,925	6,20,437	6,22,216	6,22,204	6,12,734
R-squared	0.003	0.010	0.127	0.002	0.006	0.131	0.002	0.006	0.137

Panel B. Stock level

	Dependent variable: value-weighted trading performance								
	(1)	(2) 1 Day	(3)	(4)	(5) 5 Days	(6)	(7)	(8) 10 Days	(9)
Eig. centrality	0.525**	0.488**	0.0513	1.193***	1.120***	0.975***	1.397**	1.322*	1.498**
	(2.242)	(2.337)	(0.267)	(3.303)	(3.094)	(3.614)	(2.018)	(1.821)	(2.303)
Broker volume	−0.269	−0.225	−0.0859	−1.088*	−0.989*	−1.397**	−1.710**	−1.561*	−1.877**
	(1.321)	(1.176)	(0.676)	(1.823)	(1.666)	(1.986)	(2.044)	(1.883)	(2.373)
Average trade size	0.341***	0.310***	−0.134	0.511**	0.437*	−0.136	0.776**	0.703**	0.188
	(3.165)	(3.022)	(1.140)	(2.166)	(1.960)	(0.705)	(2.160)	(1.988)	(0.827)
Time FE	Yes	No	No	Yes	No	No	Yes	No	No
Stock FE	Yes	No	No	Yes	No	No	Yes	No	No
Stock-time FE	No	Yes	No	No	Yes	No	No	Yes	No
Manager-stock-time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2,24,94,332	2,24,72,436	1,77,40,438	2,23,61,446	2,23,39,563	1,76,20,550	2,20,93,898	2,20,71,583	1,73,62,843
R-squared	0.001	0.039	0.343	0.001	0.044	0.387	0.002	0.049	0.425

We use three different values for the trading horizon T: one, five, and ten days after the trade. For each horizon, the first specification only controls for time fixed effects, the second one also includes manager fixed effects, and the third one presents the results for the most conservative specification, with manager-time fixed effects. Overall, even restricting to trades made by the same manager in the same month, we find that more central brokers tend to intermediate more profitable trades. Thus, these results cannot be explained only by the fact that better managers trade systematically with more central brokers.[17]

The results are also economically significant. For example, using the estimate in Column 6, we find that a one standard deviation increase in broker centrality increases performance by almost 15% relative to its mean (we are using the fact that the mean five-day return is 8.7 bps). This result suggests that a significant source of alpha for fund managers might be the access to better connections. Note also that the results increase in magnitude when we consider the five and ten-day horizons (i.e., comparing Column 3 with Columns 6 and 9). This fact is helpful in ruling out the hypothesis that these excess returns could be driven by differences in price impact across brokers, as this competing hypothesis would imply decreasing coefficients over time. These results might be partially attributable to a better execution by central brokers. However, this alternative hypothesis would not explain the effects being increasing over time.[18]

[17] In Table A.1 in the Internet Appendix, we report the results for the test proposed by Oster (2017) on whether the presence of omitted variables could bias our results. We find that even assuming that the omitted factors are twice as important as the observable ones, the bias-adjusted betas are still positive and economically significant. This test reassures us that our results are not driven by characteristics of the managers or the brokers that are not captured in our specifications.

[18] It is interesting to check whether central brokers are able to capture these excess returns by charging higher fees to the investors. To check if this is indeed the case, we take advantage of the fact that Ancerno also reports data on the trading fees and commissions paid by the fund managers to the brokers. This allows us to compute a measure of trading performance net of fees. We find very similar results to the ones presented in Panel A. This is suggestive of the fact that the excess returns are not

4.3. Potential non information-based explanations

In this section, we explore a set of potential explanations of our findings, which are unrelated to the informational content of the trades, while in Section 5, we present evidence supporting the hypothesis that central brokers are able to generate higher excess returns thanks to their superior access to information.

4.3.1. Central brokers intermediate higher volume

One could conjecture that central brokers are also the largest brokers, and for this reason, they can intermediate transactions more efficiently. To directly test this hypothesis, the specification in Eq. (1) includes volume intermediated by the broker over the prior six months (in logs) and the average size of the trade as controls. The results suggest that the centrality measure is capturing other dimensions than the volume the brokers intermediate.

Furthermore, in Appendix Table A.2, we show that our results are robust to including additional controls such as the number of a broker's clients, the activeness of these clients, the number of hedge funds clients, the concentration of the clients' trades, and the client's centrality measure (computed in a symmetric way relative to the broker's centrality).

4.3.2. Central brokers trade different types of stocks

Another potential explanation for the observed profitability of central broker trades may have to do with stock-level heterogeneity, including time-varying risk premia. Indeed, when we consider the trades made by the same manager at the same time through multiple brokers (Columns 3, 6, and 9 of Table 4), the results could still be explained by brokers trading different types of stocks.

To rule out this possibility, we exploit the depth of our data and obtain a finer aggregation of our regression sample at the stock-broker–manager-month level. Specifically, we compute the trading performance of each manager i trading stock k with broker j in month t, which allows us to include stock fixed effects. Formally, this is our new specification:

$$Trading\ performance_{ikjt} = \beta_1 Broker\ centrality_{jt} + X_{jt} + \theta_i + \mu_{kt} + \varepsilon_{ijt}\ , \qquad (2)$$

where μ_{kt} stands for stock-time fixed effects. Panel B of Table 4 reports the results for the one-day, five-day, and ten-day horizons. All specifications include the volume intermediated by the broker in the last six months and the average size of the trade. Columns 1, 4, and 7 control for time and stock fixed effects, Columns 2, 5, and 8 include stock-time fixed effects, while Columns 3, 6, and 9 include manager-stock-time fixed effects. The latter specification captures any time-varying heterogeneity at the stock and manager level by comparing the performance of the same manager trading the same stock in the same month with different brokers.

This finer specification also allows us to rule out another mechanism that could explain our results: time-varying risk premia for the stocks to the extent that they do not vary intra-month. Even with these more restrictive specifications, the data support H1, as the results are still economically and statistically significant: for instance, using the estimate in Column 6, a one standard deviation increase in network centrality increases five-day performance by about 11% relative to its mean.

4.3.3. Central Brokers provide better execution

We have shown that variation across managers and stocks is not able to explain away the result that central brokers tend to generate higher excess returns. One potential explanation of this advantage is the fact that central brokers might be more skilled in trade execution. Institutional investors expect brokers to optimize their trading strategies. Hence, being central in the network of relationships with institutional investors might correlate with their ability to provide better execution. For instance, central brokers might be more likely to trade at the best price during the day. Or, they could choose to trade when liquidity is the highest so as to minimize price impact.

We formally test this hypothesis in Appendix Table A.3. The main difference with the previous specifications is the definition of the dependent variable. We compute the managers' trading performance using the execution price (Columns 1 and 5) with the one using the opening price (Columns 2 and 6), the value-weighted average daily price (Columns 3 and 7), and the closing price (Columns 4 and 8) rather than the actual price at which the trade is executed. This allows us to cleanse our findings from any variation that is a result of the intra-day timing of the trades and that can be attributable to the brokers' ability to execute the trades. In all specifications, we control for manager-stock-time fixed effects to focus on the variation coming from differences across brokers. We show that, even in this case, trades through central brokers perform significantly better. Furthermore, we report the Chow test for differences in these coefficients, and we can reject the null that these coefficients are different from each other. Although better execution might still be an important factor driving the differences between central and peripheral brokers, this evidence strongly suggests that it is unlikely to be the only source of the superior performance of the trades executed by central brokers.

4.3.4. Alternative centrality measures

There are several advantages to using eigenvector centrality as a measure of centrality. First, it is used extensively in the literature on information transmission (e.g., Hochberg et al., 2007; Alatas et al., 2016), and our later findings on higher-degree information transmission justify its use. Second, eigenvector centrality does not depend for its construction on managers' performance (which is an outcome variable in our analysis) while capturing a feature of the data: smart money managers in this market are more likely to use multiple brokers, and as a result, they

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entirely captured by the brokers. Hence, central brokers possibly exploit their privileged position in the market by other means than higher fees such as attracting new clients or more volume from the same clients.

end up being more central.[19] In turn, central brokers will have access to better information through their interaction with smart managers. Third, eigenvector centrality is a parameter-free limit of Bonacich centrality, which makes it less prone to data mining. However, one might wonder how much our results depend on the specific measure of centrality that we use. Appendix Table A.4 provides specifications similar to those in Table 4, where we use alternative measures of centrality and show that our findings do not crucially rely on a single measure of centrality.

Relatedly, a concern shared by most papers in the network literature is that the network itself is endogenous, which could affect the interpretation of the results. This issue is hard to address because of the requirement of exogenous variation in the network structure for identification purposes. The robustness of our results to the inclusion of high-dimensional fixed effects, exploiting variation within manager and stock, is helpful in ruling out alternative explanations. Furthermore, given the persistence in the broker's centrality, it might be plausible to take the network as static and then study how information propagates through it as a good first-order approximation.

5. Information extraction as the source of abnormal returns

Overall, the previous findings suggest that trades intermediated by more central brokers earn positive abnormal returns that cannot be explained away by the total volume brokers intermediate, by sorting of different managers with different brokers, by stock-level characteristics, by time-varying risk of the stocks, or by brokers' execution ability. Therefore, the evidence supports H1. Still, the question remains open of how these superior returns are generated.

5.1. Informed trades

According to H2, brokers infer information from the trades of their informed clients and this behavior is more pronounced for central brokers who have better access to information. The incentive for the broker is to build a reputation as a valuable source of information and attract more business. If central brokers disseminate information that they extract from informed order flow, we should observe that in response to an informed trade, other investors are more likely to follow by executing similar trades.

To test this hypothesis, we first identify informed trades as large trades executed by hedge fund managers. We define as *large trade* any net volume traded by a manager in a specific stock, with a unique broker, over a time window of one week, which is larger than or equal to the 75th percentile of the order imbalance distribution estimated from Ancerno data in the previous six months across all broker–manager pairs (order imbalance is scaled by the weekly trading volume in the Center for Research in Security Prices (CRSP)).[20] The trade can either be a buy or a sell. We further condition on the executing manager to be a hedge fund, as these institutions are the more likely informed traders in the market. We identify hedge funds in Ancerno using the management company name.

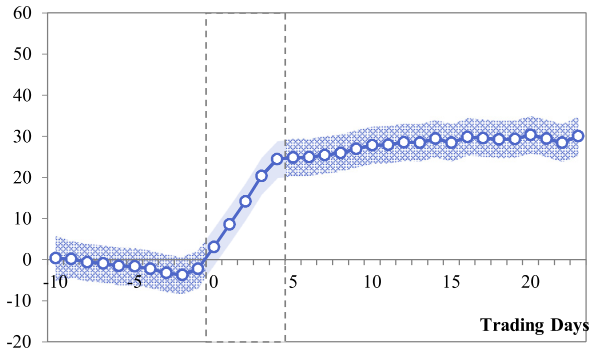

Fig. 5. This figure plots the cumulative abnormal return (in bps) of the stocks involved in a large trade before, during, and after the week in which the large trade is identified (*Week 0*), from day −10 to day 25.

One concern is that large trades might be motivated by liquidity needs. Then we first show that these trades tend to be informed trades. We do so by regressing in Appendix Table A.5 a dummy equal to one if the trade is profitable on an indicator variable identifying the large trades, controlling for stock characteristics. We find that, indeed, large trades are significantly more likely to be profitable. Furthermore, to rule out the possibility that these large trades are liquidity driven, we report in Fig. 5 the four-factor-adjusted cumulative returns for the stock before and after the big trade, at the daily frequency. We find that the stock price significantly increases with no evidence of reversal after 20 trading days. This evidence corroborates the view that the large trades that we identify are indeed informed trades.[21]

We start our tests of this information hypothesis by analyzing how the volume passing through central brokers changes around these large trades. If other traders can take advantage of the information possessed by the informed trader (called henceforth originator) and disseminated by the broker, we should observe an increase in the volumes in the same direction as the large trade intermediated by central brokers after the large trade has started.

To formally test H2, we consider the trading behavior of all the managers (called henceforth followers), other than the one generating the large trade, who trade the same stock with the same broker that executed the original large trade. We divide the sample into three subperiods: the two

[19] We estimate the correlation between average 5-day profitability for a given manager and the number of brokers that the manager uses at 0.59. Hence, we can claim that better managers use more brokers.

[20] We find very similar results when we restrict attention to the trades in the top decile. To ensure that the large trade is not the consequence of prior trading activity in the stock, we also require that in the two weeks prior to the large trade the manager's imbalances in the stock and the stock return are not "extreme," i.e., they are within two standard deviations of the mean of their distributions computed over the prior six months.

[21] Fig. A.3 reports a similar graph for 52 weeks after the event and reports separately the average returns of all trades and the average returns of profitable trades only.

Table 5
Large trades.
This table relates the trading behavior of followers after a large trade. The followers are all the managers, different from the one who generates the large trade (i.e., the originator), who trade the stock with the same broker who intermediates the large trade. We divide the sample into three subperiods: the two trading weeks preceding the week in which the large trade was made (*Before*); the period in which the large trade has started, but the originator is still trading in the same direction at a sustained pace (Competition); and the period after the originator has stopped trading, up to four weeks after the large trade week in which he initiated the trade sequence (Week 1–4). When we refer to Week 1 after the large trade, we identify the five-day trading period that starts after the end of the Competition period; Weeks 2–4 are defined consequently. In the first two columns, the dependent variable is a dummy that takes value one if the follower trades in the same direction as the originator, and zero otherwise, while in Columns 3–4, it is the log of the net dollar volume of the followers multiplied by the sign of the trade. Panel B reports the same specification but interacting the time dummies with the centrality measure. The centrality measure is standardized to have zero mean and unit variance. We include as a controls the natural logarithm of the dollar trade volume intermediated by the relevant broker in the last six months and the natural logarithm of the large trade volume, taken in absolute value (as before, scaled by the trading volume in CRSP). The most conservative specifications include stock-time and manager-time fixed effects. Panel C uses as dependent variable an indicator for whether the manager is executing the first trade after the large trade in the same direction as the Originator during the Competition week or Week 1. The dummy takes a value of 0 if the follower's first trade is in the opposite direction or it is in the same direction but after Week 1. The explanatory variables are dummy variables (Strong relation) that identify, among all the managers who are trading the stock, the ones who have a stronger relationship with the broker. We use four different proxies for the strength of the manager-broker relationship. The first three proxies identify the top quarter of the distributions of the three following variables. First, we consider the trading volume that the manager originated for the broker in the past. More specifically, we divide the volume originated from the manager by the total volume intermediated by the broker, thus obtaining the percentage volume. Then, for each broker, we sort the managers in increasing order of volume and compute the measure as the cumulative percentage volume generated by each manager and all the other managers who traded less than she did with the broker. The second measure is computed in a very similar fashion, but the dollar volume is replaced by the dollar trading commissions generated by the manager. The third measure is obtained as the average number of days that passes from two consecutive trades of each manager with the same broker, multiplied by minus one (so that it is positively related with the trading frequency). We estimate each proxy over the six months preceding the month in which the trading takes place. The last proxy is a dummy that identifies an affiliation relationship between a manager and the broker. *T*-stats based on robust standard errors, clustered at both the month and the manager level (manager level only in Panel C), are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	(1)	(2)	(3)	(4)
	Dummy=1 if follower trades in the same direction as the informed trade		Log of dollar imbalances from followers	
Competition	0.0667***	0.0633***	1.615***	1.540***
	(5.106)	(4.847)	(4.991)	(4.754)
Week 1	0.00256***	0.00255***	0.0616***	0.0616***
	(3.225)	(3.169)	(3.138)	(3.102)
Week 2	−0.00138	−0.00124	−0.0315*	−0.0278
	(1.641)	(1.533)	(1.648)	(1.516)
Week 3	−0.00184*	−0.00171	−0.0468**	−0.0437*
	(−1.718)	(−1.646)	(−1.990)	(−1.911)
Week 4	−0.00260**	−0.00241**	−0.0614**	−0.0575**
	(−2.038)	(−1.976)	(−2.083)	(−2.028)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes	No	Yes	No
Manager-time FE	No	Yes	No	Yes
Stock-time FE	Yes	Yes	Yes	Yes
Observations	2,10,19,798	2,09,99,192	2,09,64,660	2,09,44,053
R-squared	0.079	0.093	0.077	0.092

Panel B: Central vs peripheral

	(1)	(2)	(3)	(4)
	Dummy=1 if follower trades in the same direction as the informed trade		Log of dollar imbalances from followers	
Centrality × Competition	0.0267***	0.0265***	0.672***	0.666***
	(7.990)	(7.842)	(7.683)	(7.555)
Centrality × Week 1	0.000486	0.000567	0.0144	0.0166
	(0.657)	(0.762)	(0.827)	(0.951)
Centrality × Week 2	−0.00226***	−0.00216***	−0.0500***	−0.0478***
	(3.311)	(3.222)	(3.086)	(3.001)
Centrality × Week 3	−0.00281***	−0.00284***	−0.0738***	−0.0747***
	(3.271)	(3.347)	(3.761)	(3.826)
Centrality × Week 4	−0.00410***	−0.00400***	−0.101***	−0.0997***
	(3.552)	(3.475)	(3.668)	(3.602)
Centrality	0.00371**	0.00324**	0.101***	0.0919***
	(2.451)	(1.994)	(3.941)	(3.713)

(*continued on next page*)

Table 5 (*continued*)

Competition	0.0620***	0.0585***	1.496***	1.420***
	(5.360)	(5.087)	(5.257)	(5.004)
Week 1	0.00252***	0.00251***	0.0607***	0.0606***
	(3.239)	(3.181)	(3.157)	(3.121)
Week 2	−0.00136	−0.00121	−0.0311	−0.0273
	(1.510)	(1.404)	(1.524)	(1.396)
Week 3	−0.00183	−0.00170	−0.0467*	−0.0434*
	(1.613)	(1.540)	(1.864)	(1.786)
Week 4	−0.00261*	−0.00241*	−0.0617*	−0.0575*
	(1.873)	(1.813)	(1.916)	(1.863)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes	No	Yes	No
Manager-time FE	No	Yes	No	Yes
Stock-time FE	Yes	Yes	Yes	Yes
Observations	2,10,19,798	2,09,99,192	2,09,64,660	2,09,44,053
R-squared	0.079	0.093	0.077	0.092

Panel C: Relationship strength

	Dependent variable is dummy for a trade in the same direction as the Originator after the large trade during Competition or Week 1											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Strength of relationship proxy:	Ranking of manager–broker volume			Ranking of revenue share			Frequency of manager–broker interaction			Broker–manager affiliation		
Strong relation	0.0722***	0.0413***	0.0821***	0.0790***	0.0519***	0.0891***	0.0794***	0.0481***	0.0860***	0.108***	0.0796**	0.0975***
	(8.682)	(8.932)	(8.554)	(10.81)	(12.18)	(10.56)	(8.495)	(8.891)	(9.123)	(2.578)	(2.344)	(4.468)
Constant	0.243***			0.241***			0.237***			0.264***		
	(54.28)			(51.45)			(60.89)			(34.39)		
Mgr FE	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Stock FE	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Time FE	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Stock-time FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	55,99,032	55,98,851	54,53,613	55,99,032	55,98,851	54,53,613	55,99,032	55,98,851	54,53,613	55,99,032	55,98,851	54,53,613
R-squared	0.006	0.023	0.184	0.007	0.024	0.186	0.007	0.023	0.185	0.001	0.022	0.178

trading weeks preceding the week in which the large trade was made (before), which we take as baseline period; the period in which the large trade has started, but the originator is still trading in the same direction at a sustained pace (competition); and the period after the originator has stopped trading, up to four weeks after the large trade week in which he initiated the trade sequence (after). Note that the competition period starts in the week of the large trade but may potentially extend for several trading days after it has ended.[22]

In Panel A of Table 5, we report the estimates from the following specification:

$$Followers\ trading_{ikt} = \beta_0 Competition_{jt} + \sum_{\tau=1}^{4} \beta_\tau Week_\tau + \theta_{it} + \mu_{kt} + \varepsilon_{ikt}\ , \qquad (3)$$

where the dependent variable is either a dummy that takes value one if the follower trades in the same direction as the originator, and zero otherwise (Columns 1–2), or the signed log of the net dollar volume of the followers (Columns 3–4). We include as a control the logarithm of the dollar trade volume intermediated by each broker in the last six months and the logarithm of the large trade dollar volume. The specification allows us to control for heterogeneity among stocks and managers that might influence their trading behavior because we include stock-time and manager-time fixed effects. The frequency of the observations is daily. The time unit for the time fixed effects is the week.

We find that followers are significantly more likely to trade in the same direction as the informed trader during the competition period and, to a smaller extent, in the subsequent week, compared to the period before the large trade starts. Evidence of imitation in the competition week means that the followers are generating price impact while the broker is still executing the originator's trade, which

[22] To define the exact starting moment of the large trade, we look at the cumulative net volume of the originator, starting from her first trade of the week and up to each of the following trades. We compare such net volume with the past distribution of all the net volumes on that stock in the previous six months, with any individual broker, traded by any manager in our sample during a number of days that is equal to the number of trading days that has passed since the originator's first trade (i.e., we compare one-day net volumes with one-day net volumes, two-day net volumes with two-day net volumes, and so on). As soon as the net volume of the originator reaches the 75th percentile of the benchmark distribution, we consider the large trade as started. Given our definition of a large trade, it must be that the large trade starts within the large trade week. An alternative signal we use to claim that the large trade has started is the observation of three trades (three buys or three sells) on the same stock, with the same broker, during the week: as soon as the third trade happens, we deem the large trade as started, independently of the cumulative net volume at that point. After the end of the large trade week, as soon as the originator trades a quantity below the 25% of her net traded volume on the day the large trade started, we consider the large trade as finished. This includes the cases in which the originator stays one or more days without trading the stock or when she trades in the opposite direction with respect to the large trade. What we define as competition period is the time between the moment in which the large trade starts and the last trade before the large trade finishes.

adversely affects the price at which the originator is able to trade. Starting from Week 2, the followers are less likely to trade in the same direction as the originator compared to the period before the initiation of the large trade. However, Fig. A.4 and A.5 in the Internet Appendix show that the average imbalances for the originator and the followers remain in the same direction for a few weeks after the large trade. Hence, we do not find an immediate reversal of the followers' trades, which would suggest that the followers are just chasing a short-term price impact. Rather, the lack of reversal is consistent with information-motivated trades.

Panel B tests the hypothesis that these effects are even more pronounced when the central brokers intermediate the large trades. We interact the period dummies with the measure of centrality of the broker that is executing the originator's order, which we standardize to have unit variance and zero mean. In the competition week, the followers tend to trade the relevant stock in the same direction as the originator even more when central brokers execute the originator's order. For a one standard deviation increase in centrality, the probability of imitating the large trade in the Competition period increases by about 2.7%, which is a 43% increase relative to the baseline probability of imitation in that period (i.e., 6.2%). Thus, the interactions are both statistically and economically significant. This evidence corroborates the last statement in H2.

H3 puts forward an additional implication of the information channel: if brokers have access to superior information, they should release it selectively in a way that allows them to extract the highest rents. Panel C investigates this hypothesis by studying whether the followers' mimicking behavior that we show in Panel A depends on the strength of their relationship with the broker. The conjecture is that brokers have a stronger economic incentive to pass information to their best clients as a reward for their loyalty. The dependent variable is an indicator for whether the manager is executing the first trade in the same direction as the originator after the large trade during the Competition week or Week 1. Intuitively, the first followers receiving the information are able to trade early on and capture higher rents.

We use four different proxies for the strength of the manager–broker relationship measured ex ante. The first three proxies identify the top quartile in the distributions of the three following variables. First, we consider the trading volume that the manager originated for the broker in the past (Columns 1–3). More specifically, we divide the volume originated from the manager by the total volume intermediated by the broker, thus obtaining the percentage volume. Then, for each broker, we sort the managers in increasing order of volume and compute the measure as the cumulative percentage volume generated by each manager and all the other managers who traded less than she did with the broker. The second measure is computed in a very similar fashion, but the dollar volume is replaced by the dollar trading commissions generated by the manager (Columns 4–6). The third measure is obtained as the average number of days that passes from two consecutive trades of each manager with the same broker, multiplied by minus one, so that it is positively related with the trading frequency (Columns 7–9). We estimate each proxy over the six months preceding the month in which the trading takes place. Another direction to look for selective disclosure is to identify managers that have common institutional affiliation with the broker. Hence, we collect information on the asset managers that belong to the same institution of the broker, which we identify using Capital IQ and Factiva (Columns 10–12).

The estimates suggest that managers with a stronger relationship with a given broker are significantly more likely than other managers to imitate the originator's trade in the Competition week and in Week 1, consistent with H3. The effect is also economically important. For example, in Column 1, managers with the strongest relation are about 7% more likely to trade in the same direction as the originator in those weeks, relative to a baseline value for that probability of 24% (the constant in that regression).[23]

5.2. Information percolation

How does information diffuse in the market? Does it percolate from the originator's broker to other market participants than the brokers' clients? It is possible that the clients of the originator's broker execute some of their trades with other brokers, who can then alert their clients about the relevant information, and so on. In general, we expect information to spread across the network of trading relations at a decaying rate. To test this conjecture, we build a measure of the distance between brokers (nodes in the network) and study how it affects investors' likelihood to trade in the same direction as the originator. We define distance to capture the shortest path between brokers, where connections occur through managers that trade with these brokers.[24] Table 6 reports the results.

In Columns 1–3, the dependent variable is the probability of trading in the same direction as the originator; Columns 4–6 focus on dollar imbalances. The interactions between the Competition and the Week 1 dummies and the distance measure are negative and significant, suggesting that as we move away from the broker used by the originator, information diffusion decays significantly. In the data, one standard deviation of distance is roughly equivalent to one step away from the broker that intermediates

[23] To provide more details about the relationships between brokers and asset managers, we estimate in Appendix Table A.6 how the probability to add a broker or sever a relationship with one depends on the market returns, the volatility in the market, and the manager's past performance. We find that it is significantly more likely to add (drop) a broker when the market has been performing well (badly) in the past.

[24] Based on Miura (2012), the distance matrix D is defined as a |V |×|V | matrix with each entry D_{ij} equal to the length of the shortest path between vertices i and j, where |V | is the number of vertices (Brokers in our case). A path is defined as a way to reach vertex j from vertex i using a combination of edges that do not go through a particular vertex more than once. If no such path exists between vertices i and j, then D_{ij} is set to missing, signifying what is sometimes called an infinite path. D_{ii} is set to zero. Matrix D is symmetric for undirected networks. Thus, in our context, a graph is a network $G = (V, E)$, with vertices V and edges E; brokers are the vertices, with D_{ii} set to zero; a path is a combination of edges leading from one broker to another; each D_{ij}, $i \neq j$, gives the shortest path from broker i to broker j and that does not pass through another vertex more than once; edges are weighted in this network, so that stronger broker–manager relationships are given more importance.

Table 6
Information percolation through the network.
This table relates the trading behavior of followers after a large trade and broker distance along the network. Specifically, this table runs the same test found in Table 5, Panel B but with a broker's distance from the big trade broker interacted with the time period dummies. Whereas the original specification focuses on trades with the same broker as the originator, this test focuses on trades with all brokers in the network. Distance is defined as the length of the shortest path from the big trade broker to other brokers at the time of the big trade. Specifically, if the big trade broker is broker *i*, then broker *j*'s distance from the big trade broker is the (*i,j*) entry of the distance matrix computed for the month of the big trade. We focus on the largest trade (by dollar volume) on each stock within a month. In Columns 1–3, the dependent variable is a dummy that takes value one if the follower trades in the same direction as the originator, and zero otherwise; in Columns 4–6, it is the log of the net dollar volume of the followers multiplied by the sign of the trading direction. *T*-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)	(6)
	Dummy=1 if follower trades in the same direction as the informed trade			Log of dollar imbalances from followers		
Distance × Competition	−0.0210***	−0.0198***	−0.0217***	−0.515***	−0.488***	−0.526***
	(4.570)	(4.421)	(4.401)	(4.436)	(4.303)	(4.265)
Distance × Week 1	−0.000899***	−0.000804**	−0.000941***	−0.0227***	−0.0204**	−0.0240***
	(2.810)	(2.510)	(3.035)	(2.817)	(2.564)	(3.063)
Distance × Week 2	0.000345	0.000325	0.000504**	0.00838	0.00804	0.0111**
	(1.417)	(1.311)	(2.256)	(1.538)	(1.447)	(2.184)
Distance × Week 3	0.000731**	0.000664**	0.000797**	0.0163**	0.0151**	0.0181**
	(2.354)	(2.142)	(2.484)	(2.361)	(2.180)	(2.551)
Distance × Week 4	0.000638**	0.000605**	0.000654**	0.0144**	0.0138**	0.0142**
	(2.166)	(2.055)	(2.350)	(2.196)	(2.106)	(2.262)
Distance	−0.00120***	−0.00107***	−0.00120**	−0.0270***	−0.0240***	−0.0274***
	(3.525)	(3.258)	(2.577)	(3.507)	(3.257)	(2.650)
Competition	0.0785***	0.0741***	0.0819***	1.902***	1.806***	1.971***
	(4.677)	(4.537)	(4.486)	(4.554)	(4.426)	(4.363)
Week 1	0.00337***	0.00321***	0.00411***	0.0837***	0.0799***	0.105***
	(2.841)	(2.665)	(3.606)	(2.928)	(2.779)	(3.598)
Week 2	−0.000423	−0.000354	−0.00223**	−0.0151	−0.0138	−0.0512**
	(0.342)	(0.280)	(2.437)	(0.531)	(0.477)	(2.289)
Week 3	−0.00250*	−0.00231	−0.00326***	−0.0585*	−0.0553*	−0.0728**
	(1.782)	(1.597)	(2.604)	(1.921)	(1.761)	(2.568)
Week 4	−0.00164	−0.00154	−0.00298***	−0.0422	−0.0399	−0.0668***
	(1.242)	(1.153)	(2.762)	(1.418)	(1.338)	(2.664)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes
Manager FE	Yes	No	Yes	Yes	No	Yes
Manager-time FE	No	Yes	No	No	Yes	No
Stock-time FE	Yes	Yes	No	Yes	Yes	No
Observations	7,23,03,281	7,22,92,818	7,23,23,201	7,21,14,145	7,21,03,677	7,21,34,134
R-squared	0.054	0.062	0.033	0.053	0.061	0.031

the informed trade. Thus, moving from the broker that is executing the informed trade to the next one reduces the probability of taking advantage of this information by 25% (as it goes from 8% to 6%). This second-degree transmission is also helpful to motivate eigenvector centrality as a suitable proxy for how information diffuses in the network. That is, central brokers are the terminal nodes of higher-degree transmission of information. Furthermore, this analysis also provides empirical evidence that relates to the theoretical papers studying information percolation in financial markets, such as Duffie et al. (2009, 2015), Duffie et al. (2010), and especially Andrei and Cujean (2017).

5.3. Information sharing among managers?

AH1 contains an alternative interpretation for the evidence provided so far. It suggests that the informed investor passes his information to managers with whom he has some other connection. In other words, we want to test whether managers display correlated behavior (e.g., because they communicate directly with each other), irrespective of whether their trades pass through the broker that originated the large informed trade. One way to distinguish this from the broker leakage mechanism is to look at two managers who predominantly trade with the same brokers and examine whether this relation affects the likelihood that they follow each other in terms of informed trading.

If managers who use the same brokers display correlated behavior, even without an intervention from a specific broker, then we would expect a significant effect of a proxy for the overlap in broker usage (i.e., the manager similarity proxy) in specifications similar to Eq. (3). To construct the manager similarity proxy, for each manager in each month, we aggregate the volume intermediated with each broker over the prior six months and collect it into a vector of manager–broker intermediated volume. Then, for each large trade, we compute each follower's correlation with the originator in terms of the manager–broker vectors of volume. We also compute a Euclidian distance of these vectors between the originator and the followers. Because the Euclidian distance measures dissimilarity, we redefine it so that it is equal to zero for the most dissimilar manager and one for the originator. We can then interact the period dummies that identify the different times around the large trade in Eq. (3) with these similarity proxies (either the inverted Euclidian distance or correlation).

Note that in these tests, managers are similar in terms of the brokers they use but not in terms of the underlying trades; otherwise, we would be hardwiring the result. Our definition does not imply correlation in trades but correlation in the use of brokers. In fact, that correlation in brokers does not imply correlation in trades. We want to rule out manager-to-manager explanations for information leakage. We would expect two managers who use the same brokers to bump shoulders in trading circles and be likely to trade information with each other or at least be more aware of each other's large trades. That is, the originator is more likely to inform a more similar manager of its large trade, or the follower is more likely to be aware of a more similar manager's large trade.

Appendix Table A.7 reports the results. We find no effect of manager similarity on the probability of trading in the same direction as the large trade. We conclude that, conditional on having a relationship with the originator's broker, the fact that the originator has many brokers in common with another trader does not affect the likelihood that this trader will follow in the direction of the large trade. This evidence, therefore, does not seem to support AH1.

5.4. Similar investment styles or public information?

To provide further evidence that the evidence in Table 5 is unlikely to be driven by the followers tracking the same investment styles as the informed trader, as stated AH1, we check that these results hold even when we restrict attention to stocks that have not been previously traded by the followers but were heavily traded by the informed investor. That is, we focus on stocks that are unlikely to be part of both groups' typical strategies. More specifically, we keep in the sample only large trades performed on stocks that we deem as usual for the originator, and we consider only followers for which these stocks are deemed as unusual.

To assess whether a stock is usual or not for a manager, we look at the manager's volume in the stock in the previous six months as a percentage of the total dollar volume traded by the manager. We then adjust this value to take into account the total number of stocks traded by the manager in the period. Finally, we consider as unusual for a manager all the stocks whose adjusted percentage volume lies below the 10th percentile of its distribution across all stocks/months in our sample. On the other hand, we consider as usual stocks for a manager all the stocks whose adjusted percentage volume lies above the 50th percentile of the same distribution. Appendix Table A.8 presents the results. We show that even for this very restrictive subsample, followers tend to trade in the same direction as the originator, especially during the competition period and when the large order is executed by central brokers. The fact that we find similar evidence even in this sample is suggestive that the correlation among these investors' trades is unlikely to be due to the fact that the originator and the follower adhere to similar investment styles.[25],[26]

To rule out the possibility that the traders are all reacting to the same common information, Appendix Table A.10 excludes days in which there are earning announcements for the stock as well as days in which analysts following the stock change their recommendations. The results are unaffected, suggesting that AH1 is not supported in the data.

AH2 predicts that the research department of the broker produces the fundamental information about the stock, which the brokers' clients receive as part of brokerage services. This might be a relevant channel that might be driving some of our results. Although we cannot definitely rule it out, we can make some progress by collecting data on any report made by analysts working for the brokers, e.g., analyst recommendation and earnings forecast, and exclude from our main sample of large informed trades the stocks for which the broker has ever produced one of these reports. As shown in Appendix Table A.11, the sample is significantly reduced, but the main results are unchanged. This finding suggests that the brokers are not producing the information themselves; in fact, it would be difficult to imagine that the broker could ever pass any valuable information to the asset managers if its research department did not follow the stock at all.[27]

[25] We also provide tests for the other usual-for-broker and usual-for-manager and unusual-for-broker and usual-for-manager cuts of the data in the Internet Appendix and find similar results.

[26] We also exploit variation in the size of the trade relative to the size of the manager. Large managers may be less concerned about leakage than small trades for whom a large trade represents a bigger fraction of the portfolio. We would then expect large managers to make less effort to hide their trades, e.g., executing through peripheral brokers. To verify this conjecture, we identify a large (small) manager as one that exhibits average trade size measured over the six months leading up to the big trade month that is above (below) median across managers. Furthermore, for the small managers, we focus on informed trades that are in the bottom quartile of the trades in terms of volume to be sure that these are less important for other market participants (labeled "unimportant trades"). Fig. A.6 shows histograms for the number of events in the different quartiles of broker centrality for the two groups of traders. We find that large trades for large managers are more likely to be executed by central brokers, while unimportant trades are more likely to be executed by peripheral brokers, which corroborates the view that smaller traders make a bigger effort to avoid leakage. We also estimate the baseline specification of Table 5 for the two different samples and report it in Appendix Table A.9. We find the effects to be 2.5 larger for the large trades by large managers (Panel A) than for the unimportant trades by small managers (Panel B). Furthermore, the effects are stronger for more central brokers only for the large managers, while the effects are not significant for the small ones. These results further corroborate the information leakage hypothesis.

[27] Relatedly, to corroborate the view that the large informed order really constitutes the event that triggers the imitation by the followers, we shift the timeline of our event window to one month before the large trade and report the baseline specification in Appendix Table A.12 (Panels A and B). We do not find any significant trading of the followers in that stock. By showing the lack of correlated trades in absence of the large trade, this "placebo" contributes to rule out the alternative hypothesis that followers and originators always trade in the same direction because of correlated trading styles.

5.5. What if the originator is affiliated?

Because imitation occurs during the competition period while the originator is still carrying out his trade, the followers create a negative price externality. Hence, imitation is not per se desirable for the originator. Thus, we conjecture that if imitation is the result of information leakage, brokers will avoid, or reduce, its occurrence if they have an institutional tie to the originator. To test this conjecture, we employ Capital IQ and Factiva to identify the funds that have the same institutional affiliation as the brokers.

Appendix Table A.13 reports the baseline regressions for the probability of imitating the originator (Panel A) and the dollar imbalances (Panel B) for different types of originators. Columns 1–4 of both panels restrict attention to originators that are affiliated to the broker who execute their trades. Columns 5–8 show the results for nonaffiliated originators. We also differentiate between central brokers (Columns 1–2 and 5–6) and peripheral ones (Columns 3–4 and 7–8). For both dependent variables, we find that, when the informed trader is affiliated with a central broker, there is no imitation during the competition period or afterwards. Notice that not only is the coefficient statistically insignificant but also its magnitude is just a fraction of the baseline coefficients. Interestingly, for the large trades originated by other nonaffiliated clients, we find that there is significant imitation.

These results also help to rule out alternative hypotheses that hinge on brokers leaking information involuntarily, e.g., during the search for counterparties to the large trade. If information leakage was only the result of normal market making activities, such as contacting potential counterparties to fill the informed order, we should not observe heterogeneous effects depending on the identity of the originator.

5.6. Leaking information about activists' trades

An activist stake buildup, i.e., the time when activist investors accumulated their holdings in a target firm, provides another useful setting to test the information leakage hypothesis for at least three reasons. First, activists' target companies tend to experience significant price changes once the activists' strategies are publicly disclosed (see, e.g., Brav et al., 2008). In this sense, knowledge that the activist is building up a position is valuable. Second, there is a clear date after which the information about the activists' taking an interest in a company becomes public. Third, the activists have ten days to file a 13D form with the SEC upon reaching a 5% stake in the company they are targeting. Hence, there are ten days in which the only other market participant that has first-hand knowledge about the activist's trades is the broker through which these trades are executed.

We collect information from the 13D filings between 1999 and 2014.[28] These filings contain the name of the activists and the stock they bought. Using the ADV forms from the SEC, along with the commercial hedge fund databases TASS and HFR, we are able to extract information about the broker with which the activists trade. Using the list of activists' brokers, we can identify these brokers in Ancerno.

If brokers release information about activists' trades, we should expect other traders to buy the stock of the target company before the 13D is filed, that is, when the information is still not public. We test this conjecture in a regression setting and report the results in Table 7. The dependent variable is either a dummy identifying "Buy" trades (odd columns) or the signed log of dollar net volume (even columns). We consider an event window of 60 trading days before and after the filing. We investigate investors' trading behavior by differentiating among three time periods: the day on which the 13D is filed (Filing day), the 10 trading days before the filing (Just before), and the period that goes from 60 to 10 trading days before the filing (Before). The reference period is the time after the filing, once the information is publicly released.

We interact the time dummies with a dummy (Strong relation) that identifies, among all the managers who are trading the stock, the ones who have the strongest relationship with the activist's broker. Based on H3, we expect brokers to have a higher incentive to share the information with their best clients. The four different proxies are defined as in Panel C of Table 5.

Consistently across dependent variables and specifications, we find a positive value for the coefficient of the interaction between the Just before dummy and the relationship strength variable. In other words, the activist brokers' best clients buy more of the target stock than the other managers right before the 13D filing, compared to the period after the 13D filing. We find no difference in trading intensity in the other periods. This evidence strongly suggests that these investors were made aware of the interest in that particular stock by the broker who executed the activist's trades.

To be sure of capturing any time-invariant characteristic at the manager and stock level, we control for manager and stock fixed effects in addition to time fixed effects (odd columns). Furthermore, in our most conservative specification, we include stock by time fixed effects (even columns), which captures any other time-varying characteristic of the stock, such as its liquidity or the release of other news, which might induce investors to change their positions on that particular stock. Our results hold even in the most conservative specifications.[29]

5.7. Incremental price impact from imitation

Given that the prior analysis supports the hypothesis that brokers leak information, we next provide an assessment of the costs for the originator of this kind of broker behavior. Specifically, we quantify the additional price impact that the informed trader is facing due to the followers imitation, which is the result of the information leakage.

[28] We are grateful to Vyacheslav (Slava) Fos for providing the list of activists filing the 13D.

[29] In untabulated results, we find that these findings are significant only in the subsample of central brokers, further confirming that the central brokers are more prone to share order flow information.

Table 7
Activists.
In this table, we test the trading behavior of Ancerno traders before the filing of a 13D schedule from an activist investor. The dependent variable is either a dummy identifying buy trades (odd columns) or the log of net dollar volumes from the manager, multiplied by 1 in case of a net buy volume or by −1 in case of a net sell volume (even columns). In all panels, we consider a time range of 60 trading days before and after the filing. The time dummies indicate the day on which the 13D filing happens (Filing day), the 10 trading days before the filing (Just before) and the period that goes from 60 to 10 trading days before the filing (Before). The imbalances are computed at the day level and then averaged over the four time periods (Before, Just before, Filing day, and after the filing date), obtaining in this way a sample at the 13D filing/Ancerno manager/time period level; a 13D filing is identified by an activist, the stock involved in the filing and the filing date. We interact the time dummies with a dummy (Strong relation) that identifies, among all the managers who are trading the stock, the ones who have a stronger relationship with the activist's prime broker. We use four different proxies for the strength of the manager–broker relationship. The first three proxies identify the top quarter of the distributions of the three following variables. First, we consider the trading volume that the manager originated for the broker in the past. More specifically, we divide the volume originated from the manager by the total volume intermediated by the broker, thus obtaining the percentage volume. Then, for each broker, we sort the managers in increasing order of volume and compute the measure as the cumulative percentage volume generated by each manager and all the other managers who traded less than she did with the broker. The second measure is computed in a very similar fashion, but the dollar volume is replaced by the dollar trading commissions generated by the manager. The third measure is obtained as the average number of days that passes from two consecutive trades of each manager with the same broker, multiplied by minus one (so that it is positively related with the trading frequency). We estimate each proxy over the six months preceding the month in which the trading takes place. The last proxy is a dummy that identifies an affiliation relationship between a manager and the activist's prime broker. A positive value for the coefficient of the interaction between the time dummy and the relationship dummy suggests that the prime broker's best client bought more/more frequently than the other managers in that period, compared to what they did after the 13D filing. *T*-stats based on robust standard errors, double clustered at both the time and the manager level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dummy identifying buy trades	*Log of dollar imbalances*	*Dummy identifying buy trades*	*Log of dollar imbalances*	*Dummy identifying buy trades*	*Log of dollar imbalances*	*Dummy identifying buy trades*	*Log of dollar imbalances*
Strength of relationship proxy:	Ranking of manager–broker volume		Ranking of revenue share		Frequency of manager–broker interaction		Broker–manager affiliation	
Strong relation	−0.0051	−0.1670	−0.0026	−0.1420	0.0005	−0.1180	−0.0339***	−0.660*
	(0.524)	(0.804)	(0.241)	(0.610)	(0.0456)	(0.508)	(3.479)	(1.840)
Strong relation × Before	0.0011	0.0126	0.0000	0.0036	−0.0114	−0.2260	0.0670**	1.143*
	(0.118)	(0.0623)	(0.00432)	(0.0180)	(0.967)	(0.889)	(2.082)	(1.834)
Strong relation × Just before	0.0363***	0.682**	0.0306**	0.508*	0.0258**	0.550**	0.0548***	1.205***
	(3.095)	(2.445)	(2.535)	(1.838)	(2.184)	(2.066)	(7.247)	(7.662)
Strong relation × Filing day	0.0008	0.1060	−0.0017	0.0749	−0.0093	0.0451	0.0385**	0.709**
	(0.0310)	(0.179)	(0.0629)	(0.127)	(0.403)	(0.0860)	(2.468)	(2.029)
Before	−0.0061	−0.0561	−0.0059	−0.0541	−0.0035	−0.0049	−0.0063	−0.0604
	(0.674)	(0.266)	(0.662)	(0.263)	(0.376)	(0.0232)	(0.756)	(0.303)
Just before	−0.0200**	−0.477**	−0.0184*	−0.430**	−0.0175*	−0.447**	−0.0107	−0.3060
	(2.051)	(2.227)	(1.901)	(2.018)	(1.758)	(2.037)	(1.174)	(1.557)
Filing date	0.0069	0.0181	0.0076	0.0226	0.0095	0.0220	0.0055	0.0242
	(0.401)	(0.0436)	(0.439)	(0.0556)	(0.561)	(0.0543)	(0.378)	(0.0664)
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	No	No	No	No
Stock-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No
Event FE	No	No	No	No	No	No	No	No
Observations	96,810	94,865	96,810	94,865	96,810	94,865	96,810	94,865
R-squared	0.13	0.122	0.13	0.122	0.13	0.122	0.13	0.122

We compute price impact as the execution shortfall, i.e., the percentage difference between the transaction price and a pretrade benchmark price for the originator (e.g., Keim and Madhavan, 1997). The underlying assumption is that the benchmark gives the price at which the originator can trade if no price impact occurs. Hence, the execution shortfall estimates the loss for the originator due to the followers' negative price externality.[30] We use the following benchmark prices: (i) the first transaction price of the first day on which the large trade takes place, (ii) the first placement price on the same day, and (iii) the open price on the same day. In more detail, on each day in which the large trade is taking place, we compute the daily implementation shortfall for the originators' trade, using the benchmark price from the first day. We then aggregate the daily shortfalls by taking the volume-weighted average across days and express them in basis points.

Then, we regress the implementation shortfall on the followers' volume to capture its impact on the originator's trading costs. We report the estimates in Table 8. In all specifications, we express the followers' volume as a fraction of the CRSP dollar volume traded in the competition period. We also control for the originator volume relative to the CRSP dollar volume traded in the competition period

[30] The execution shortfall contains a component of price impact that is due to the originator's trading activity. For this reason, our regressions control for the originator volume.

Table 8
Price impact during large trades.
This table reports results on the price impact experienced by large trade originators. We construct the following daily price impact measures: (i) the execution shortfall based on the first transaction price, (ii) the execution shortfall based on the first placement price, and (iii) the execution shortfall based on the first open price; each of these benchmarks are measured on the first day of the large trade. We aggregate the measures by taking the volume-weighted average across transactions on a given day and express them in basis points. In each specification, we regress the price impact measures on the aggregate volume of other managers (followers) relative to the CRSP dollar volume traded in the competition period. We control for the originator volume relative to the CRSP dollar volume traded in the competition period and the Amihud ratio of the stock, estimated over the previous month. Explanatory variables are standardized to mean zero, unit variance. Standard errors are clustered by manager, stock and month. *T*-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)	(6)
	First transaction		First placement		Open	
Follower volume	18.709***	17.452***	17.275***	14.794***	11.624***	9.961***
	(12.320)	(12.076)	(10.901)	(9.769)	(8.347)	(9.126)
Originator volume	16.693***	16.711***	14.441***	17.067***	3.768***	4.872**
	(15.585)	(16.573)	(9.472)	(9.446)	(2.694)	(2.451)
Amihud ratio	4.418***	5.192***	13.664***	16.821***	14.664***	20.472***
	(4.615)	(4.669)	(8.477)	(11.167)	(8.148)	(12.445)
Stock FE	Yes	No	Yes	No	Yes	No
Manager FE	Yes	No	Yes	No	Yes	No
Broker FE	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No
Mgr-Mth FE	No	Yes	No	Yes	No	Yes
Bkr-Mth FE	No	Yes	No	Yes	No	Yes
Observations	3,91,774	3,90,628	3,91,774	3,90,628	3,91,577	3,90,432
R-squared	0.138	0.146	0.200	0.197	0.208	0.179

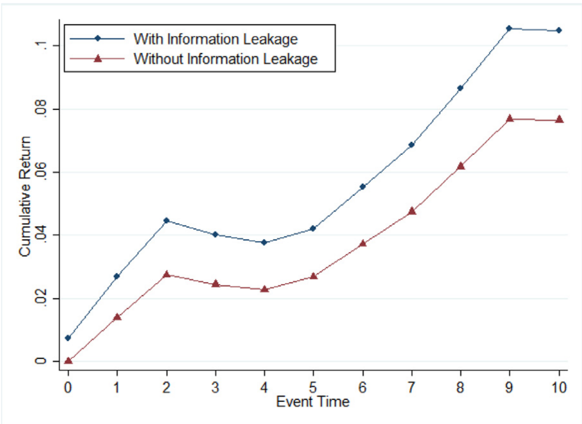

Fig. 6. This figure plots the actual cumulative four-factor adjusted return (blue circles) and the hypothetical cumulative return in the case of no other asset managers trading in the same direction (red triangles). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and the Amihud ratio of the stock, as they are both important determinants of price impact. Time, manager, broker, and month fixed effects are included as well.

We find that the coefficient on followers' volume is both economically and statistically significant. A one standard deviation increase in the followers' volume increases price impact by about 10–19 basis points, depending on the specification. This effect represents an increase of about 10—30% with respect to the mean of these price impact measures. Using the fitted values from similar regressions at the daily level, we can provide a graphical description of the difference in price paths between the case with and without information leakage. Fig. 6 plots the actual cumulative returns for the first ten days of the large trade averaged across large trades and compares it with the hypothetical cumulative return derived by setting the followers' volume to zero. The figure effectively shows that the transaction costs significantly increase for the informed trader due to the followers' imitation.

6. Why do informed investors stick with leaky brokers?

6.1. The club hypothesis

When considering the theoretical soundness of a market equilibrium in which brokers leak order flow information, one may wonder why an informed asset manager is willing to trade with brokers that tend to leak to other market participants. The conjecture we lay out in H4 suggests that informed investors find it profitable to join a "club" for which the membership fee is the leakage of their private information, but the benefit is the eligibility to receive tips about other investors' informed trades. The broker would enforce this cooperative equilibrium across subsequent rounds of trading. In particular, the broker can exclude from the club the managers that never share their private information and reward with more tips the managers that are more willing to share.

We can formally test the club hypothesis by analyzing whether being an informed trader in the past (i.e., information supplier) predicts being a follower in the future (i.e., an information receiver). Table 9 shows that this is indeed the case, with investors that have acted as originators in the past being more likely to be among the followers in the next quarter and even more so to be the followers that imitate the informed trade during the competition period.

Next, we can study whether the cooperative equilibrium is sustainable by studying whether the expected benefits from receiving information from the broker outweigh the expected cost from imitation for the originator of the

Table 9
Club.
This table relates, for each investor/broker pair, the absolute value of dollar imbalances traded as a follower in a given quarter and the absolute value of dollar imbalances traded as an originator in the previous quarter, controlling for the lagged dependent variable. When computing the dependent variable, we consider all dollar imbalances traded as a follower (Columns 1–2); only the volumes traded in the same direction as the large trade (Columns 3–4); only the volumes traded in the same direction as the large trade and during the competition period, i.e., the time when the large trade has started but the originator is still trading (Columns 5–6); and only the volumes traded in the same direction as the large trade and during the first week after the competition period (Columns 7–8). We require that the volume traded as an originator in the previous quarter to be greater than zero. *T*-stats based on robust standard errors, clustered at the manager level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Dependent variable is the absolute value of dollar imbalances traded as a follower in a given quarter							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Restriction on imbalances:	All imbalances		Same direction of the large trade		Same direction / During Competition period		Same Direction / During Week 1 after Competition	
Lagged abs. imbalances as originator	0.0740***	0.104***	0.0546***	0.0700***	0.0131***	0.0117***	0.0479***	0.0502***
	(13.72)	(18.35)	(13.76)	(26.44)	(17.34)	(19.71)	(21.40)	(19.18)
Lagged depended variable	0.441***	0.282***	0.336***	0.170***	0.0905***	0.0344*	0.201***	0.120***
	(16.73)	(14.86)	(9.637)	(9.305)	(3.064)	(1.898)	(8.367)	(6.781)
Broker FE	Yes	No	Yes	No	Yes	No	Yes	No
Manager FE	Yes	No	Yes	No	Yes	No	Yes	No
Broker–Manager FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	38,786	38,350	38,786	38,350	38,786	38,350	38,786	38,350
R-squared	0.446	0.495	0.355	0.424	0.187	0.233	0.277	0.320

large trade. We compute the NPV of the decision to participate in the club by comparing the returns of being a follower to the losses as originator. Using the frequency of originator and follower trades in a manager–broker relation, we estimate the probabilities of being a follower and that of being an originator.[31] Panel A of Appendix Table A.14 gives the distribution of the probabilities of follower and originator activity across manager–broker pairs that involve club members. We note that the average probability of being a follower for club members is about 13.9%, while the probability of being an originator is, on average, 7.4%. Panel A also gives the average performance for followers using different approaches to compute returns for robustness purposes.[32] On average, the followers make between 11.3 and 18.4 basis points per trade, looking at value- and equal-weighted returns, respectively. For the losses as an originator, we use the estimates of the price impact from imitation in Table 8, which are, on average, 15.16 basis points per dollar invested for a normal level (i.e., a one standard deviation) of followers' activity. Finally, we compute the NPV of club membership at the manager–broker level as the return from trades as follower times the frequency of trading as a follower minus the loss from price impact times the frequency of trades as originator. On average, the NPV is positive and statistically significant.[33] Thus, we conclude that joining the club is a rational decision for investors, consistent with H4.

Finally, to gage the gains accruing to a manager from being a follower relative to other activities, we can compute the dollar profits on the capital invested during the Competition period and Week 1 on follower trades on large-trade stocks and divide them by the profits from all trades on all stocks in the same month. Again, we focus on a five-day holding period and report the results in Panel B of Appendix Table A.14. We find that, on average, follower trades account for a sizable 26% of all monthly profits. Moreover, the returns per dollar invested in follower trades are almost twice as large as the returns from all trades. We conclude that trading based on information leakage is a very attractive strategy for these managers.

6.2. The benefits of leaking for brokers

Information leakage involves a reputation cost for the brokers. We expect, therefore, that brokers are able to extract some benefit from leakage, if they decide to engage in this activity. To assess the brokers' incentive to leak,

[31] We designate managers as club members based on whether they have been both a follower and an originator with a broker at any point in the history of their relationship. To compute the probabilities, we count the number of trades that the manager executes as a follower and as an originator with the broker and divide those figures by the total number of trades executed with the broker. The mean of this distribution across broker-manager pairs gives us our final estimate of these probabilities.

[32] Specifically, we look at both equal- and value-weighted trading performance across the Competition period and Week 1. Equal-weighted performance is simply the average return for trades made within the window for a manager with a broker across the entire sample. For value-weighted performance, we first compute the trading-volume-weighted return within each large trade event for a follower and then take the equal-weighted average across each manager–broker pair. For all trades, we set a five-day holding period. Results remain similar with longer holding periods.

[33] The NPV ranges between and one and two basis points per dollar invested over the five-day horizon on which we compute returns. These numbers are small due to the short horizon. More intuitively, the expected return from receiving the information is, on average, between 40% and 127% larger than the expected loss from information leakage, depending on whether one uses value- or equal-weighted returns.

Table 10
Gains for the brokers.
This table displays the gains for brokers from intermediating large trades. In Panel A, we investigate how much the broker is gaining in terms of commissions generated around big trades. We consider all stocks involved in a big trade for a broker on a day. That is, we aggregate commissions on stocks in the [−10,−1] period, those in the Competition period or Week 1, and those in Weeks 2–4 at the daily level. Then, we divide these commissions by the total amount of commissions generated on that day. Thus, the dependent variable is the broker's share of total commissions that is being generated on stocks involved in big trades, expressed in percent. We include as independent variables time period dummies for stocks currently in the Competition period or Week 1 ("Competition or Week 1") and stocks currently in Weeks 2–4 ("Weeks 2-4") of their big trade events. The baseline period is the [−10,−1] days leading up to the beginning of the competition period of a big trade event. We also include a dummy if the commission is coming from a manager who is a "Follower" or traded in the same direction as the big trade during the competition period. Panel B relates the number of times a manager is a follower a particular broker within a month with the probability that she will execute a large trade with the same broker within the same month. The dependent variable is a dummy taking the value of 1 if the manager executes a large trade (acts as an originator) with the same broker as the one he is a follower, and zero for trading relationships with all other brokers within a month. The main independent variable is the number of times that manager is a follower for other big trades executed by the broker within the same month. We include as a control the natural logarithm of the large trade volume. All explanatory variables are standardized to unit variance. *T*-stats based on robust standard errors, clustered at the manager level, are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Shares of commissions coming from big trade stocks

	(1)	(2)
	Commission shares	
Follower X Competition and Week 1	1.735***	1.904***
	(45.29)	(9.278)
Follower X Weeks 2–4	−0.532***	−0.523***
	(14.48)	(7.691)
Competition and Week 1	0.208***	0.186**
	(7.465)	(2.473)
Weeks 2–4	0.992***	1.036***
	(32.09)	(9.689)
Follower	−1.286***	−1.426***
	(50.51)	(10.20)
Constant	2.729***	
	(110.9)	
Broker FE	No	Yes
Week FE	No	Yes
Observations	4,26,814	4,26,813
R-squared	0.021	0.108

Panel B: Relation of followers and likelihood of executing a big trade

	(1)	(2)
	Probability of trading as Originator with broker i	
No. of informed trades as follower	0.0260***	0.0283***
	(6.650)	(3.686)
Big trade size	0.000139**	2.41E−06
	(1.990)	(0.0320)
Constant	0.0544***	
	(77.57)	
Manager FE	No	Yes
Time FE	No	Yes
Broker FE	No	Yes
Observations	2,11,17,342	2,11,17,341
R-squared	0.013	0.028

we measure the additional commissions that are generated following information leakage. That is, for each broker, we aggregate daily commissions generated on stocks involved in large trades and express that as a share of total daily commissions for the broker. We find that, on average, 10.6% of the brokers' daily commissions in the period following the large trade (Competition week to Week 4) are generated by orders on stocks involved in large trades, excluding the trades from the originator. This evidence strongly suggests that the additional trading volume generated by information leakage represents a significant fraction of the brokers' profits.

In the same vein, we can also formally test whether followers during large-trade events significantly impact broker commissions. In Panel A of Table 10, the dependent variable is the share of commissions that comes from large-trade stocks over the total commissions that a broker earns on a given day. We focus on three time periods: the ten days leading up to the Competition period (the "before" period), the Competition period and Week 1, and Weeks 2–4. We also create an indicator for whether the commissions are coming from followers' trades. We find that commissions from followers' trades during the Competition and Week 1 periods are significantly higher than

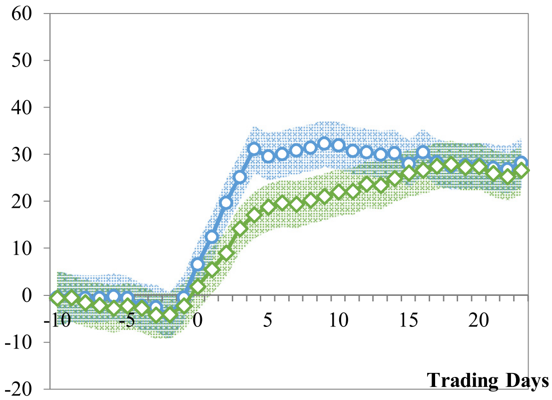

Fig. 7. This figure plots cumulative abnormal return (in bps) of the stocks involved in a large trade before, during, and after the week in which the large trade is identified (starting on day zero). We separate between large trades intermediated by central broker (in blue circles) and peripheral brokers (in green diamonds). *Central broker* here means all the brokers whose eigenvector centrality lies above the 60th percentile of its distribution. The areas in blue and red are the 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

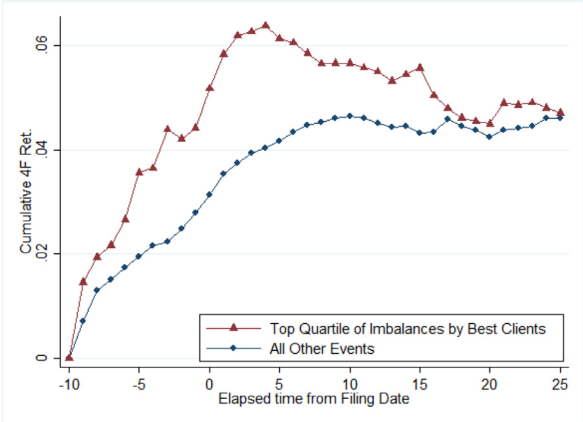

Fig. 8. This figure plots the abnormal returns for the [−10, 25] days window around activists' 13D filings, for the stocks that are in the top quartile of imbalances by the activist's broker best clients (red triangles), and for all other events (blue diamonds). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

commissions from other investors. This evidence further confirms that brokers significantly increase their revenues thanks to their clients trading on their tips.

We can also test whether brokers gain indirectly by securing access to future business and future informed trades. Panel B of Table 10 shows that the managers that are more likely to be followers, measured by the number of trades as followers with a specific broker, are significantly more likely to execute their informed trades as originators with the same broker. The number of informed trades variable is standardized to have zero mean and unit variance. For a standard deviation increase in the number of trades, the likelihood rises by 2.5%, which is quantitatively large, as it is a 50% increase relative to the baseline.

Overall, brokers gain a significant fraction of their commissions thanks to their practice of leaking information; furthermore, they also gain from their clients being more likely to execute their informed trades through them in the future.

7. Implications of information leakage for price behavior

The evidence so far supports the hypothesis that brokers leak the information that they extract from the observation of informed trades. These findings raise the question of whether central brokers' behavior improves price discovery. By disseminating private information, asset prices may reflect this information faster, as conjectured in H5. The evidence of price impact in Table 8 implies that the followers' volume has a significant impact on prices. Our goal in this section is to examine how this channel affects the speed at which prices reach the new fundamental level.

To address this question, Fig. 7 plots the average cumulative abnormal return of the stocks involved in a large trade before, during, and after the week in which the large trade is identified. We separate between large trades intermediated by central broker (line with circles) and peripheral brokers (line with diamonds). Relying on our previous findings, we make the identifying assumption that information leakage takes place most prominently with central brokers. The graph shows that, when a large trade executes through a central broker, the price achieves its new level after about a week. In contrast, for peripheral brokers, after the first week, the stock price has only achieved two-thirds of its long-term level. Hence, price discovery is 50% faster through central brokers. Therefore, this evidence corroborates the hypothesis that information dissemination by central brokers enhances price discovery, and the effect is sizeable.

Our study of trading activity during the period in which activists build their stake in a target company provides a more fitting context to quantify the importance of broker information leakage for price discovery. This setup has two clear advantages in helping us addressing this question. First, there is a clear date after which the information becomes public. Second, there is an interval of time, ten days, during which the broker and the activist are the only ones to be informed about the activist stake buildup. In other words, the prefiling period is characterized by private information, which is then released to the public with the filing. Then, we can compare the returns originated in the prefiling period with those over the whole sample period. In absence of information leakage, we should expect the market to react to the filing and to incorporate that information in the subsequent days. In contrast, when brokers leak this information, the price should incorporate part of that information in the days preceding the filing.

Fig. 8 plots the four-factor-adjusted returns for the [−10, 25] day window around activists' 13D filings, for the stocks that are in the top quartile of imbalances by the best clients of the activist's broker, and for all the other quartiles. The identifying assumption in this analysis is that high volume by best clients in the pre-filing period is a symptom of information leakage. We contrast this situation to all events in which the best clients' volume is lower, capturing situations of nonsignificant information leakage. The figure shows that, whenever the best clients of the activist's broker trade aggressively in the target stock, the stock return rises more steeply before the filing so that a larger fraction of the total event return is generated before the filing date. Specifically, the cumulative returns over the [−10,25] window is 5.19% for all events. When the best clients' imbalance are in the top quartile, about 4% out of 5.19% is realized in the ten days before the filing. That suggests that information leakage accounts for about 77% of the total reaction of prices to the activist stake buildup.

Appendix Table A.15 provides additional estimates from regressions relating price reactions around 13D filing dates to the followers' volume during the ten days before the 13D filing. This analysis ensures that the estimates for the importance of the information-leakage channel are not driven by other confounding factors. First, we consider the return in the ten-day prefiling period [−10,−1]. Intuitively, if followers' volume predicts returns during the period in which information should still be private, then we can claim that information leakage improves price discovery in the prefiling period. We find that this is indeed the case. We also find that the followers' volume negatively predicts the market reaction to the public announcement of the activist's campaign in the short [−1,1] windows (Column 2) and long [−1,25] window (Column 3). This evidence suggests the followers' trades push the price slightly above its long-run level causing overshooting.[34] The overshooting is evident also in Fig. 8 when focusing on the price path in case of large trading volume by the followers. Finally, consistent with the rest of the evidence, in Column 4, higher follower imbalance increases the prefiling return relative to the return over the entire window.

8. Conclusion

The paper presents three main findings. First, it shows that trades placed through more central brokers generate significantly higher abnormal returns. Second, we present evidence that is consistent with the conjecture that these excess returns result from central brokers disseminating the information they capture by observing informed investors' trading. Finally, we show that information sharing may accelerate price discovery by incorporating information into prices more quickly.

These results have several implications. First, since Kyle (1985), a slow execution is considered optimal to minimize price impact. However, our results show that there exists an important trade-off between price impact and information leakage due to the intermediation of the brokers who might act on their own best interest, and disseminate information about order flow. Second, our findings highlight that an important source of returns for fund managers in the stock market is not information production per se. Rather, some managers appear to free ride on the information provided by stock brokers, which in turn is acquired thanks to their privileged position in the trading network. Finally, our results contribute to the debate on the value of delegated portfolio management and the nature of the services that asset managers provide to their clients. Since building a relationship with brokers requires a scale and a reputation that is not accessible to retail investors, the fact that a connection to the right brokers generates investment performance provides a "justification" for delegated portfolio management.

Overall, the evidence in the paper suggests that the broker network has important implications for how information is impounded into prices and for the generation of trading profits. Future theoretical research should probably take this channel into account when describing the percolation of private information in financial markets.

[34] Follower imbalance is divided by its standard deviation, and the coefficient is divided by 10 for readability. In particular, an increase in follower imbalances, equivalent to the average imbalances in our events, increases the pre-filing period return by 49 bps, and it reduces the immediate market reaction by 78 bps, while the market reaction over the window [−1, 25] decreases by 52 bps.

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