The Relevance of Broker Networks for Information Diffusion in the Stock Market[1]

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Abstract

This paper shows that the network of relationships between brokers and institutional investors shapes the information diffusion in the stock market. We exploit trade-level data to show that trades channeled through central brokers earn significantly positive abnormal returns. This result is not due to differences in the investors that trade through central brokers or to stocks characteristics, as we control for this heterogeneity; nor is it the result of better trading execution. We find that a key driver of these excess returns is the information that central brokers gather by executing informed trades, which is then leaked to their best clients. We show that after large informed trades, a significantly higher volume of other investors execute similar trades through the same central broker, allowing them to capture higher returns in the first few days after the initial trade. The best clients of the broker executing the informed trade, and the asset managers affiliated with the broker, are among the first to benefit from the information about order flow. This evidence also suggests that an important source of alpha for fund managers is the access to better connections rather than superior skill.

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1. Introduction

How information is generated by market participants, disseminated, and finally incorporated into prices has been the subject of extensive literature in finance, 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 the 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 the brokers' role in disseminating the information that they acquire from their clients is at best unclear. The 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.[2] This paper shows that brokers indeed play a key role in shaping information diffusion in the stock market.

Recent theoretical developments, such as Babus and Kondor (2016) and Yang and Zhu (2016), have modeled the way in which intermediaries and fast traders take advantage of their access to information about other investors' trades. Although information about prices is readily disseminated in equity markets, brokers' vantage point 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 trading relations – are in a better position to observe the informational flow than peripheral ones. Then, brokers might have an

[2] Recently, Credit Suisse and Citi were accused of leaking information about customer orders to other market participants (see, for instance, http://www.nytimes.com/2016/02/02/business/dealbook/regulators-arent-done-with-dark-pool-investigations.html?_r=0).

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 trading through central brokers able to generate higher returns thanks to their superior access to order flow information? What role do brokers have in affecting how information is incorporated into prices? This paper investigates these questions 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 by providing 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 such as the market excess return, SMB, HML, and the momentum factor. We find that this portfolio generates a significant alpha of about forty 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. To address these concerns, our second set of results take 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 restricting to trades made by the same manager in the same timeframe, i.e. controlling for manager-time fixed effects.

The possibility remains that broker centrality correlates with stock characteristics. For instance, central brokers might specialize in more illiquid stocks. We rule out this explanation in the regression analysis. In particular, we exploit further the granularity of our data and include manager-stock-time fixed effects in the most restrictive specifications. Even when we consider the same stock traded by the same manager in the same timeframe, we find that central brokers are associated with more profitable trades. This evidence strongly suggests that the main results are not fully explained by the fact that different brokers might trade stocks with different characteristics.

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. This suggests that the source of the returns does not derive from the broker's ability to execute a large volume of trades, but rather from its pivotal position in the network of connections tying market participants.

A different source of advantage for the central brokers, which might influence our results, is their superior trade execution quality; for instance, central brokers might execute trades at the best price during the day or when liquidity is the highest. We test this hypothesis by computing the managers' trading performance replacing the execution price with the opening price, the value weighted average daily price, and the closing price. We then obtain a measure of trading performance, which is not affected by the intraday market timing ability of the broker. We show that, even in this case, trades through central brokers perform significantly better, suggesting that better execution cannot be the main difference between central and peripheral brokers driving our results.

Having established that trades executed through more 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 (2013) 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. 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. First, if information percolates via the central brokers, we should observe a higher correlation among the trades executed by traders that use those brokers. Specifically, if central brokers disseminate the information contained in informed trades, uninformed traders should behave similarly to the informed ones. To test this hypothesis, we first identify informed trades as 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; which strongly suggests that these are indeed informed trades. We show that other investors (*followers*) are significantly more likely to trade with the *same* broker in the same direction of the large trade if the trade is executed through a central broker. Hence, trading activity following the large order is more correlated when the latter passes through a central broker, suggesting that central brokers are more likely to pass along the information about the large trade to other investors. Furthermore, we show that the followers tend to reverse their trades after two weeks. This suggests that their decision to trade is more likely to be opportunistic, i.e. exploiting the information passed by the broker, rather than based on long-term views.

An additional 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. The first 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. Supporting selective disclosure, we show that the asset managers that are affiliated with the broker executing the large trade are among the first ones to imitate the large trade.

Based on similar logic, we should observe that especially the best clients of the central brokers receive the information. The best clients are those with which the broker made more profits in the past and from which it expects to continue to receive business in the future. Accordingly, we measure the strength of the broker-manager relationship in three ways: by the past volume intermediated by the broker for a given manager, by the commission paid by a given manager to the broker, and by the frequency with which the given manager trades with the broker. We find strong evidence that the managers with the strongest relationships with central brokers capture, on average, higher excess returns for each trade. Moreover, they are also more likely to be among the first ones to follow in the footsteps of informed trades by trading in the same direction. The effects are also economically significant; a one standard deviation increase in the centrality of the broker increases the performance of its best clients by 25% relative to their five-day trading performance. This suggests that a significant fraction of the alpha generated by institutional investors might not be due to superior trading skills, but rather a result of their connection to central brokers. This relation enables uninformed managers to free ride on the information collected by central brokers from other institutional investors.

An additional implication of the information channel is that brokers intermediating the large trades would reduce the occurrence of back running if the large trader and the broker are part of the same institution. Then to test this hypothesis, we restrict attention to large trades where the manager has institutional ties with the broker, and we find that the broker preempts the competition by other traders and, rather, it fosters liquidity provision. That is, the volume by the other investors trading through the broker moves in the opposite direction of the large trade.

One concern is that the originator and the followers trade in a correlated fashion because they follow similar styles, as in Barberis and Shleifer (2003), and they choose central brokers to implement these trades. To rule out this possibility, we show that our results hold even when we restrict attention to stocks that have not been previously traded by the followers, but that were heavily traded by the originator. In these cases, it is unlikely that the large trader and the followers are tracking similar investment styles.[3]

We also provide two additional placebo tests. First, to corroborate the idea that large trades constitute indeed an "information shock", we estimate our main specification shifting the event date to four weeks before the actual large trade. We find that the correlation between the followers and the originator of the large trade breaks down. This indicates that the observed correlation among traders' strategies is unlikely to be driven by factors other than the large trade itself.

Second, we also check if the followers employ other brokers to imitate the originator's trades. The idea is that if they receive information by the broker executing the large trade, they will compensate him by channeling most of their trades through this same broker in order to pay him most of the commissions. Consistent with this hypothesis, we find that followers concentrate their trades with the broker that executed the large trade, suggesting a mutual exchange of favors among the parties.

The previous results centered on the idea that information is generated by unusually large trades which then percolates through the brokers to other investors. Another natural setting in which we test the information hypothesis is the release of corporate news. Informed traders might be trading right before the news announcement, which would reveal their private information to the brokers. That is, if central brokers convey private information, volume should be higher through central brokers at times of information release. We focus on earning announcements and analyze how order imbalances vary during the 10 days before and after the announcement. We find that positive imbalances in the period following the good news

[3] Notice that this alternative hypothesis would also need to explain why these managers tend to trade with the same broker, why the best clients and the ones affiliated tend to imitate more strongly, and why the followers tend to revert their trades after few days.

are significantly higher for central brokers. Interestingly, we find informed investors, proxied by those with higher past performance, trade more forcefully *before* the event with central brokers in the right direction. We interpret this evidence as suggesting that central brokers have better access to information also because they are more likely to intermediate informed trades before news events.

Finally, the information advantage enjoyed by central brokers might be the result of their own ability to directly produce the information: central brokers might devote higher resources to their research and company analysis department, and disseminate it to their clients. To test whether this explanation is solely responsible of the observed profitability of trades through central brokers, we focus on stocks that are outside the broker's usual domain. Indeed, we find that central brokers are able to generate higher excess returns than peripheral brokers even when we restrict attention to stocks that the brokers have not dealt with frequently in the past. For the stocks traded less often by the broker, it is more likely that the broker will try to capture fundamental information through the investors trading these stocks rather than through their analysts, who have not covered that stock in the past. This analysis, therefore, seems to rule out that central brokers are solely responsible for the production of the fundamental information that leads to higher trading profits.

Overall, the previous results have 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. At the same time, fund managers seem to be able to generate significantly higher performance thanks to their connections to brokers that have access to information, rather than for their superior stock-picking or market-timing abilities.

We then investigate the price formation process and test whether this behavior by central brokers also affects price efficiency. We document that informed trades lead to faster stock price movement when they are intermediated by central brokers rather than peripheral ones. Specifically, we follow DellaVigna and Pollet (2009) and analyze the response ratio to large trades, defined as the ratio between the cumulative Carhart (1997) four-factor adjusted returns on day 5 and day 25 since the large trade. We find that the response ratio increases with the broker centrality, suggesting that prices adjust more quickly after large trades when these are executed through central brokers. Furthermore, we also find that the price is also more likely to overshoot for about ten days after the large trade before partially reverting. These results are consistent with our interpretation of the evidence that brokers tend to generate higher volume in the same stock by disseminating information about the large trade to their clients.

Overall, our findings indicate that, although we are analyzing an exchange where prices are public information, and not an OTC market, intermediaries play a key role in the acquisition and dissemination of private information, which they extract from order flow and, more generally, from the interaction with their clients. Since we show that informed traders, the ones placing large trades, are able to capture higher excess returns when they use central brokers, their incentives to produce information are not adversely affected by the brokers' activity, in contrast to what would occur in a model à la Grossman and Stiglitz (1980). Furthermore, by disseminating the information to their best clients, brokers are also making sure that prices incorporate the information faster. This faster revelation of information can be beneficial for, and even encouraged by, the informed trader, as described by Ljungqvist and Qian (2016) and Kovbasyuk and Pagano (2015) in the context of short selling.

Few 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 over-the-counter 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 more central broker-dealer are able to learn more than peripheral ones; and confirm the idea presented in Yang and Zhu (2016) that traders might back-run informed 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, Malamud and Manso (2009, 2015), Duffie, Giroux, and Manso (2010), and especially, Andrei and Cujean (2016), who show how information percolation might lead to momentum and reversals. Also related is Walden (2016) who shows that agents who are more closely connected have similar trades in the context of a dynamic noisy rational expectations model, in which information diffuses through a general network of agents. 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.[4]

Lately, the study of trading networks has made some forays into the empirical finance literature as well. The recent paper by Di Maggio, Kermani, and Song (2016) studies the network of dealers in the corporate bond market. 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

[4] 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, Vayanos and Zwiebel (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, Banerjee, Chandrasekhar, Hanna and Olken (2016)), technology adoption (Bandiera and Rasul 2006; Duflo, Kremer, and Robinson 2004; and Conley and Udry 2010) or microfinance, and public health (e.g., Munshi 2003; Bandiera, Barankay, and Rasul 2009; Banerjee et al. 2013; and Kremer and Miguel 2007).

to become less profitable.[5] Other recent papers have studied the role of the network in different markets. For instance, Li and Schürhoff (2014) study the municipal bond market and highlight the tradeoff that investors face: central dealers have higher execution speed, but charge higher spreads; whereas peripheral dealers are less expensive, but slower. Hollifield, Neklyudov, and Spatt (2014), instead, identify a core-periphery network structure in the securitization market and show that pricing appears to be more favorable at the center of the network. Afonso, Kovner, and Schoar (2013) describe the network of relations in the interbank lending market, separating between spot and long-term borrowing transactions. They show that the latter insulate borrowers from liquidity shocks. Finally, Hendershott, Li, Livdan, and Schürhoff, (2016) study the transactions of insurance companies with corporate bond dealers and show a tradeoff between order flow concentration and dealer competition for best execution.[6]

All of the existing evidence is for OTC markets, while we analyze the U.S. stock market and provide evidence of the mechanisms through which the network of broker-investors relationships affects returns: information diffusion. Goldstein, Irvine, Kandel, and Wiener (2009), using an earlier version of our data, provide a useful description of the institutional brokerage industry. They show that institutions value long-term relations with brokers. Also, consistent with our results, the best institutional clients are compensated with the allocation of superior information around changes of analyst recommendations.

[5] A related work is Gabrieli et al. (2014), which studies liquidity reallocation in the European interbank market and documents a significant change in the network structure around the bankruptcy of Lehman Brothers.

[6] 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. This literature, which is not directly related to the theme of this paper, owes much to the seminal paper by Cohen, Frazzini, and Malloy (2010). The authors show that sell-side analysts with school ties to senior corporate officers are able to produce more accurate earnings forecasts. Many are the contributions in this literature and a full review is out of the scope of this paper. For example, Fracassi and Tate (2012) show that firms with more powerful CEOs are more likely to appoint directors with social ties to the CEO, and this behavior harms firm performance. Shue (2013) shows that managers who graduated from the same MBA class share similar managerial decisions. Lerner and Malmendier (2013) argue that a higher share of entrepreneurial peers in the business school class reduces entrepreneurship of a given graduate. Nguyen (2012) shows that when CEO and some of the directors belong to the same social network, the CEO is less likely to be dismissed for poor performance.

Our results are also consistent with Li, Mukherjee, and Sen (2016) who show that analysts at brokerages houses with which company insiders place their trades have an informational advantage. Also related, Chung and Kang (2016), who use monthly hedge fund returns to document comovement in the returns of hedge funds sharing the same prime broker, and with Ozsoylev, Walden, Yavuz and Bildik (2014) who employ data from the Istanbul Stock Exchange to show that more central individual investors earn higher returns and trade earlier than peripheral investors with respect to information events. A complementary approach to study how information is shared in the market has recently been proposed by Boyarchenko, Lucca, and Veldkamp (2016) who build a model and calibrate it to the Treasury auction data. They use this model to quantify counterfactuals about policy intervention that would ban information sharing between dealers and with clients.[7]

The remainder of the paper is organized as follows. Section 2 describes the data sources and summary statistics and Section 3 demonstrates that trading through more central brokers leads to higher abnormal returns. Section 4 presents evidence showing that these abnormal returns are mainly generated by the ability of more central brokers to collect and disseminate information. Section 5 presents the implications for price behavior, while Section 6 provides concluding remarks.

2. Data and summary statistics

In order to analyze whether and how the broker network shapes trading outcomes and information diffusion in the market, one needs a detailed trade-level dataset that also reports

[7] Also related are the papers studying how cooperation and reputation among intermediaries affect liquidity costs in exchange markets. Battalio et al. (2007) documents an increase in liquidity costs in the trading days surrounding a stock's relocation to the floor of the exchange, while Pagano and Roell (1992) and Benveniste et al. (1992) demonstrate that reputation attenuate the repercussions of information asymmetries in trading and liquidity provision. More recently, Henderson et al. (2012) investigates the repeated interactions between placement agents (investment banks) and investors in the initial pricing of convertible bonds, whereas Cocco (2009) provides evidence from the interbank market that banks provide liquidity to one another at times of financial stress.

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.[8] There are several advantages to this dataset. 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 dataset 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), Anand, Irvine, Puckett, and Venkataraman (2012, 2013), have shown that the characteristics of stocks traded and held by Ancerno institutions and the return performance of the trades are comparable to those in 13F mandatory filings.

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); the stock 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

[8] 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 no attempt is made to identify the underlying institutional names.

focus on the trades executed through the top 30 brokers by volume in the prior six months.[9] These brokers intermediate more than 80% of the whole volume in the dataset.

Figure 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 average manager uses about 8 brokers to execute its trades. The average broker, instead, has more than 110 fund managers as clients. The investors on the periphery are the ones that are connected with only one or two brokers.

Our main measure of network centrality is the eigenvector centrality (Bonacich, 1972, Katz, 1953, Bonacich, 1987, and Bonacich and Lloyd, 2001). This variable takes into account all direct and indirect trading partners (i.e. fund managers and other brokers) and is computed by assigning scores to all brokers in the network. A 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. Figure 2 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.

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

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 percent 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. Figure 3 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 three-thousand 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 with lower market capitalization, that are more illiquid, as captured by higher Amihud (2002) illiquidity measure, that 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, Table 1B reports the characteristics of the managers trading with central and peripheral brokers. First of all, 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 trade prevalently with central brokers trade a higher total and net volume. Furthermore, these funds also exhibit higher past trading performance. Finally, we identify the hedge funds in the database and distinguish between active and passive managers, and show that hedge funds and more active asset managers are more likely to trade with central brokers. All these results corroborates the view that centrality correlates with brokers' access to information from as they interact prominently with traders that are more likely to be informed.

3. Network Centrality and Profitability

In this section, we provide evidence that central brokers are associated with significantly positive abnormal returns for institutional investors.

3.1 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 month, 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 will indicate heavily sold stocks (through the broker) and a score of ten will indicate heavily bought stocks. If a stock is not traded by any broker in the quarter then we remove it from our set. 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 brokers group and the peripheral brokers group. 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 broker groups we compute a long/short, value-weighted portfolio by 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.[10]

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 2 reports these results. We provide four specifications: raw returns and alphas from one-factor, three-factor, four-factor models (Carhart, 1997). Across specifications, we find a positive and significant performance 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 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.

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

One potential explanation for the observed outperformance of central 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 towards 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. Figure 4 plots the returns over a twelve-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 à la Coval and Stafford (2007).

3.2 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 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 the returns of each trade at the manager-broker-day level. Then, we estimate the following specification

$$Trading\ Performance_{ijt} = \beta_1 Broker\ Centrality_{jt} + X_{jt} + \gamma_t + \theta_i + \varepsilon_{ijt}\,, \tag{1}$$

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.[11] 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.

The main coefficient of interest in equation (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. 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 3, 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).

We use three different values for the trading horizon T: 1, 5, and 10 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.

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 5-day return is 8.7

[11] 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.

bps). Note also that the results increase in magnitude when we consider the 5 and 10-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. It also seems unlikely that these excess returns are attributable to a better execution by the more central brokers; since this hypothesis would not explain the effects being increasing over time either.

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. Table A.1 in the appendix reports our baseline specification with the net trading performance as dependent variable. A smaller or less significant coefficient would suggest that central brokers take advantage of their position in the network by generating rents predominantly for themselves. However, we find very similar results to the ones presented in Panel A. This is suggestive of the fact that the excess returns are not 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.

3.3 Potential Explanations

In this subsection, we explore a set of potential explanations of our findings, which are unrelated to the informational content of the trades, while in Section 4 we present evidence supporting the hypothesis that central brokers are able to generate higher excess returns thanks to their superior access to information.

3.3.1 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, we include in the previous specification the 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.

Intuitively, centrality captures brokers who are connected with fund managers who use multiple brokers to execute their trades. Hedge funds are more likely to use multiple brokers and to be more informed than other institutional investors, such as pension funds, insurance companies, and mutual funds. Brokers who intermediate a higher volume of trades, instead, tend to be more connected with large institutional investors who employ fewer brokers and are more likely to be long-term investors. This is the reason why centrality proxies for brokers' access to informed order flow and is not perfectly correlated with volume.

3.3.2 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. 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 3), 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:

$$Trading\ Performance_{ikjt} = \beta_1 Broker\ Centrality_{jt} + X_{jt} + \theta_i + \mu_{kt} + \varepsilon_{ijt}\ ,$$

which allows us to include stock-time fixed effects μ_{kt}. Panel B of Table 3 reports the results for the 1-day, 5-day, and 10-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 premiums for the stocks to the extent that it does not vary intra-month. Even with these more restrictive specifications 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 5-day performance by about 11% relative to its mean.

3.3.3 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 better at executing investors' trades. Institutional investors expect brokers to optimize their trading strategies. Hence, being central in the network of relationships with institutional investors might be correlated 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 Table 4. The main difference with the previous specifications is the definition of the dependent variable. We compute the managers' trading performance using the opening price (Columns 1 and 2), the value weighted average daily price (Columns 3 and 4) and the closing price (Columns 5 and 6) 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, suggesting that better execution cannot explain away our results.

3.4 Who Benefits the Most?

Having established that central brokers are able to generate higher excess returns, we investigate who benefits the most from trading with central brokers. Intuitively, we should observe the clients with the strongest relationship capturing higher returns than those trading only occasionally with the brokers. We capture the strength of the broker-manager relationship in three different ways. First, we compute the volume intermediated by the broker for the manager in the previous six month and rank this measure in deciles. Second, we also measure the strength of the broker-manager relationship by taking into account the commissions paid by the manager to the broker in the previous six months and create a percentile ranking of this variable. Third, we identify the best clients as the ones that execute their trades with the broker more frequently and compute the number of days between two consecutive trades in the prior six months and multiply by minus one to obtain a measure of relationship strength. Notice that all of these measures are extremely persistent suggesting that relationships between brokers and asset managers are valuable and not easily substitutable. Although these measures are all correlated, they capture different dimensions of the broker-manager relationships.

Table 5 reports the results for the following specification:

$$
\begin{aligned}
&Trading\ Performance_{ikjt} \\
&\qquad = \beta_1 Broker\ Centrality_{jt} \times Relationship_{ijt} + \beta_2 Broker\ Centrality_{jt} \\
&\qquad\qquad + \beta_3 Relationship_{ijt} + \theta_i + \mu_{kt} + \varphi_j + \varepsilon_{ijt}\ ,
\end{aligned}
$$

where $Relationship_{ij}$ is based on volume in Columns 1-4, on commissions in Columns 5-8, and on the frequency of the interaction broker-manager in Columns 9-12. In all of these specifications we include the broker fixed effects φ_j. For each relationship measure, the first specification includes time and broker fixed effects. The second specification also includes stock-level controls such as the Amihud illiquidity measure, the stock market capitalization, the analyst coverage and the trade size. The third specification substitutes these controls with stock fixed effects, while the fourth specification is the most restrictive as it includes stock-time fixed effects.

We find strong evidence that the managers with the strongest relationships with central brokers capture, on average, higher excess returns for each trade. Table A.2 in the appendix reports a different specification in which we interact the centrality measure with a dummy identifying the different quartiles of the relationship strength measures. The fourth quartile captures the strongest tie between investors and brokers. We find that the investors without a strong relationship with the central brokers capture no benefits at all by trading through more central brokers, whereas the ones in the top two quartiles are the ones able to earn significantly higher returns. This is important because it suggests that the brokers create an uneven playing field by selectively disclosing their information only to a subset of their clients.

4. Information Collection 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. This evidence leaves the question open of how these returns are generated.

To understand how central brokers are able to generate higher excess returns we turn to the theoretical literature for potential mechanisms. Recent theoretical studies such as Babus and Kondor (2016) show that central dealers can learn faster from the transactions they execute, increasing their trading gains, while Yang and Zhu (2016) show that investors can back-run informed traders by learning through order-flow.

Thus, both theories indicate as one potential source of returns for the central brokers the information that they can infer from the trades of their informed clients. In fact, we can imagine an informed trader submitting an order through a broker, who can infer the informational content of the trade and spreads it to other clients. The incentive for the broker is to build a reputation as a valuable source of information and attract more business.[13] One may think that the informed clients would not like their information to be spread to other investors. However, if the informed investors have capacity constraints, they may actually solicit other investors to trade in the same direction, so that prices reach the new equilibrium faster, as it has been suggested by Ljungqvist and Qian (2016) in the context of short selling.

4.1 Informed Trades

If central brokers disseminate information gathered by informed traders, we should observe that in response to an informed trade, other investors are more likely to follow by executing similar trades when the informed trade passes through a central broker. In order 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

[13] Recently, brokers have also generated profits by directly selling information about the order flow to institutional investors.

75^{th} percentile of the order imbalance distribution estimated in the previous six months across all broker-manager pairs (order imbalance is scaled by the weekly trading volume in CRSP).[14] We further condition on the executing manager to be a hedge fund. We identify hedge funds in Ancerno using the management company name.

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 Table A.3 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 Figure 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 twenty trading days. This evidence further suggests that the big trades are indeed informed trades.

We start our analysis of this information hypothesis by analyzing how the volume passing through central brokers changes around these large trades. We expect that 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 intermediated by central brokers after this large trade.

We formally test this hypothesis by considering the trading behavior of all the managers (called henceforth *followers*), other than the one who generates the large trade, who trade the same stock with the same broker who executed the original large trade. We divide the sample into three sub-periods: 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

[14] 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.

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.[15]

Formally, we report in Panel A of Table 6 the results of the following specification:

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

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 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.

We find that followers are significantly more likely to trade in the same direction of the informed trader during the competition period. We find a somewhat smaller effect also for

[15] 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-days net volumes with two-days 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.

the subsequent week. This means that the followers are generating price impact while the broker is still executing the originator's trade, which adversely affects the price at which the originator is able to trade. Conversely, we find that the followers unwind their trades in the following weeks, starting in the third week after the large trade. This trading behavior is consistent with an opportunistic strategy aiming to profit from the initial price appreciation due to the originator's trade.

Panel B tests the hypothesis that these effects are even more pronounced when the central brokers intermediate the large trades. We interact the time dummies with the measure of centrality of the broker that is executing the originator's order. We find that followers tend to trade the relevant stock even more when central brokers execute the originator's order; indeed, the interactions are large and statistically significant. This evidence further suggests the role of central brokers in intermediating large informed orders and disseminating this information to other asset managers.

4.2 Similar investment styles?

To provide evidence that these results are unlikely to be driven by the followers tracking the same investment styles as the informed trader, we check that these results hold even when we restrict attention to stocks that have not been previously traded by the followers, but that were heavily traded by the informed investor. That is, we focus on stocks that were not previously tracked by both groups of investors. 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 tenth 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 fiftieth percentile of the same distribution. Table 7 presents the results. We show that even for this very restrictive subsample, followers tend to trade in the same direction of 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 comovement among these investors' trades is unlikely to be due to the fact that the originator and the follower track similar investment styles.

4.3 Placebo Tests

To test if the large informed order really constitutes the shock 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 Table 8. 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' test corroborates our interpretation of the results that the followers have been tipped off by the broker executing the large informed trade.

The conjecture that the broker intermediating the large trade leaks information to its other clients suggests an additional placebo test.[17] We run similar specifications to the ones in Panels A and B of Table 6 and focus on the trades that are executed through brokers that are different from the broker that intermediated the large trade. In this case, we expect the trading to be less correlated with the large trade. This conjecture is confirmed, indeed, we find that in the competition period, the probability of the other trades to be in the same direction as the

[17] This table is available upon request.

large trade, as well as the imbalances, is order of magnitudes smaller than when we look at the volume intermediated through the original broker. Moreover, in the periods following the big trade, we do not observe any significant correlation.

4.4 Who follows the informed trader?

We also test if the brokers discriminate among their clients, e.g. they might provide the information about the incoming informed trader earlier to their best clients. In Table 9, we test this hypothesis in two ways. First, knowing the names of the asset management funds, we employ information from Capital IQ and Factiva to identify the funds that have the same institutional affiliation as the brokers. Intuitively, if there is leakage of information from the brokers to other asset managers, then it is plausible to expect that the ones belonging to the same institution of the broker are the first to benefit from it.

To test this hypothesis, in Panel A, we regress the delay in minutes after the *large trade* on a dummy identifying an *affiliation* relationship between the broker who intermediated the large trade and the manager who acts as a follower. The delay is defined as the time passing from the large trade up to the first time other managers (followers) trade the stock. We include as a control the natural logarithm of the dollar trade volume intermediated by each broker in the last six months and the natural logarithm of the large trade dollar volume, taken in absolute value. The most conservative specification is presented in Column 6 where we include manager-time, stock-time, and broker fixed effects. We show that the asset managers that are affiliated with the broker executing the large trade are among the first ones to imitate the large trade. This is suggestive that indeed brokers seem to favor their closest clients: the ones belonging to the same institution.

For the analysis in Panel B of Table 9, we exploit the same three measure of relationship strength that were introduced in Table 5. For each measure, the first column includes time, manager, and stock fixed effects, the second one includes manager-time fixed effects, and the third column adds broker fixed effects. We find consistent evidence that the best clients of the brokers are significantly faster in imitating the informed trader when the latter executes its trades through a central broker. Again, central brokers seem to discriminate to the advantage of their best clients.

4.5 News Events

A further implication of the information hypothesis is that we should observe traders to be more active with central brokers around news events. That is, if central brokers convey private information, volume should be higher through central brokers at times of information release. Table 10 focuses on earning announcements and analyzes how order imbalance varies during the 10 days before the announcement (Columns 1-5), the day of the announcement (Columns 6-10) and 10 days after the event (Columns 11-15). We also distinguish between positive and negative earnings surprises through the dummy variable "Positive". We find that positive imbalances in the period following the good news are significantly higher through central brokers. This evidence is consistent with the conjecture that central brokers generate an informational advantage at times of news releases, which is then exploited by the traders that do business with them.

How is this informational advantage generated? If the central brokers make inference from informed trades, we should expect informed investors to trade more forcefully *before* the event with central brokers. To test this conjecture, we perform exactly the same analysis as in Panel A, but we restrict attention to the managers in the top quartile of performance in the last 6 months, with the idea that top performers are the ones that have access to better information. We find that even *before* the news events, informed managers significantly increase their imbalances with central brokers. The results survive after controlling for manager as well as stock fixed effects. We interpret this evidence as suggesting that central brokers have better access to information because they are more likely to intermediate informed trades before news events.

4.6 Broker producing the information?

Overall, the previous results have 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.

However, we also investigate if the brokers produce the information themselves by differentiating stocks based on the frequency with which they are traded by the brokers. The idea is that stocks that are traded more often by the brokers are more likely to be covered by their research divisions. Then, if most of the excess returns are generated by these stocks it would suggest that the brokers rather than the managers generate the information that gets disseminated through the market.

In Table A.4, we regress the managers' trading performance on the interaction between the brokers' centrality measure and a dummy variable equal to one if the stock traded is in the bottom decile of those traded by the broker in the last quarter. As in the baseline regressions of Table 3, we perform this analysis at the 1-day, 5-day and 10-day horizons and control for fixed effects absorbing variation at the manager-time and stock level. We find consistent evidence with the results in Table 3. This result suggests that it is unlikely that the brokers are generating the information themselves, rather the managers might be the primary source.

5. Implications for Price Behavior

We have provided evidence establishing that central brokers are able to generate excess returns thanks to the information they gather by observing informed trades. This raises the question of whether central brokers' behavior improves price discovery. On the one hand, by disseminating private information faster, asset prices might reflect this information more effectively. On the other hand, brokers might lead to overshooting as they share their information with multiple managers who can then trade on this and move prices away from fundamentals.

We start analyzing this question in Figure 6 by showing the average cumulative abnormal return of the stocks interested by 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 triangles) and peripheral brokers (line with circles). The shaded areas identify the standard errors. The graph shows that when a big trade passes through a central broker the price achieves its new level more quickly. One can contrast this with the price behavior with peripheral brokers suggesting that, after the first week, the stock price has only achieved two thirds of its long-term level. In brief, central brokers seem to be associated with a faster movement of prices to their equilibrium level. Therefore, this evidence corroborates the hypothesis that information dissemination by central brokers might enhance price discovery.

We further test this possibility by studying the adjustment of prices after the large informed trade. We follow DellaVigna and Pollet (2009) and construct the price response ratio after a large trade, defined as the ratio between the cumulative four-factor-adjusted returns on day 5 and day 24. The idea is that as the price incorporates information faster, we should observe a higher response ratio, i.e. the cumulative returns after few days are not very different from the returns achieved a few weeks after the event.

Figure 7 plots the coefficients of a regression relating the response ratio to the deciles of the brokers' centrality. We find that the response ratio increases with the broker centrality, suggesting that prices adjust more quickly after large trades when these are executed by central brokers. In unreported results, we find this relation to be statistically significant. Moreover, the figures shows that the response ratios are larger than 100% for more central brokers, confirming the evidence of slight price overshooting that appeared in Figure 6.

Overall, these results suggest that central brokers speed up the price discovery process, but may induce some overshooting in the short run.

6. Conclusion

This paper presents four main findings. First, it shows that trades placed through more central brokers generate significantly higher abnormal returns. Second, we provide evidence that these higher returns are concentrated among the fund managers highly connected to the central brokers, e.g. their best clients. Third, 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 enhance market efficiency by incorporating information into prices more quickly.

One of the implications of these findings is 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.

Overall, the evidence in the paper suggests that the network of brokers in the market has important implications for how information is impounded into prices and for the generation of trading profits.

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Table 1. Summary Statistics

This table reports the summary statistics for different subsamples. 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 key stats for the stocks traded through central and peripheral brokers.

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	5'569
CUMUL. VOLUME (% Ancerno)	82.66%	1.44%	81.43%	82.66%	83.38%	5'569
PRICE IMPACT (bps)	10.52	12.52	3.87	9.37	16.02	5'568
TRADING FEES (cents)	2.87	1.15	1.95	2.57	3.65	5'477
TRADING FEES (bps)	11.96	11.96	11.96	11.96	11.96	5'477
TRADING TIME (seconds)	16'321	4'189	13'614	16'239	19'442	5'569
VOLUME PER TRADE (usd)	372'120	221'241	233'544	312'321	450'588	5'569

Panel B: Central vs. Peripheral Brokers

	CENTRALITY Below Median		CENTRALITY Above Median		CENTRAL vs PERIPHERAL
Variable	**Average**	**StdDev**	**Average**	**StdDev**	
EIG. CENTRALITY	0.0570	0.0296	0.1565	0.0685	0.0995 ***
VOLUME (% Ancerno)	2.10%	2.00%	3.43%	2.41%	1.33% ***
PRICE IMPACT (bps)	10.01	11.54	11.04	13.41	1.03 ***
TRADING FEES (cents)	2.98	1.09	2.75	1.19	-0.24 ***
TRADING FEES (bps)	12.42	4.80	11.48	5.33	-0.94 ***
TRADING TIME (seconds)	16,349	4,358	16,293	4,014	-56
VOLUME PER TRADE (usd)	351,159	181,904	393,118	252,925	41,959 ***

Panel C: High vs. Low Volume

	VOLUME Below Median		VOLUME Above Median		HIGH vs. LOW VOLUME
Variable	**Average**	**StdDev**	**Average**	**StdDev**	
EIG. CENTRALITY	0.1018	0.0811	0.1115	0.0624	0.0097 ***
VOLUME (% Ancerno)	0.96%	0.32%	4.55%	2.03%	3.59% ***
PRICE IMPACT (bps)	11.61	14.47	9.44	10.11	-2.17 ***
TRADING FEES (cents)	3.16	1.20	2.58	1.01	-0.57 ***
TRADING FEES (bps)	13.12	5.27	10.81	4.62	-2.31 ***
TRADING TIME (seconds)	16'024	4'728	16'617	3'549	592 ***
VOLUME PER TRADE (usd)	415'795	257'786	328'617	166'536	-87'178 ***

Panel D. Stocks

	Stocks traded by Central Borkers		Stocks traded by Peripheral Borkers		CENTRAL vs PERIPHERAL	
Variable	**Average**	**StdDev**	**Average**	**StdDev**	**Obs**	**Difference**
MARKET CAP.	16.78	34.59	16.02	33.49	22,500,187	-0.76 ***
AMIHUD PAST 12M	0.00013	0.00622	0.00014	0.00659	22,498,168	9.196E-06 ***
AMIHUD	0.00008	0.01128	0.00010	0.01277	22,690,587	1.745E-05 ***
ANALYST COVERAGE	13.36	8.08	13.30	8.15	20,486,038	-0.06 ***
STD.DEV. Of ANALYST EST.	7.85%	16.58%	8.28%	17.24%	20,034,710	0.43% ***

Table 1B. Broker Choice by different classes of Manager

This table reports the average eigenvector centrality for different classes of managers. 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 ADJ. CHURN RATIO), size (NET VOLUME and TOTAL VOLUME), information (PAST PERFORMANCE and HEDGE FUND) and degree of *activeness* (ACTIVE and ADJ. ACTIVE).

Average Eigenvector Centrality of the Brokers chosen by different classes of Manager

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
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

Table 2. Portfolio Results

This table reports the coefficient estimates of the alpha of our *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-brokers portfolio and selling the peripheral-brokers 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. 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

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

	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

Table 3. Returns and Brokers' Volume

This table regress 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. 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 both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Manager Level

Dependent Variable: Value-weighted trading performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1 Day			**5 Days**			**10 Days**		
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	633,603	633,591	624,101	629,936	629,925	620,437	622,216	622,204	612,734
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)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1 Day			**5 Days**			**10 Days**		
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	22,494,332	22,472,436	17,740,438	22,361,446	22,339,563	17,620,550	22,093,898	22,071,583	17,362,843
R-squared	0.001	0.039	0.343	0.001	0.044	0.387	0.002	0.049	0.425

Table 4. Execution

This table regresses the value-weighted trading performance at different time horizons (in basis points) on our centrality measures. Columns (1)-(2) present the results when we use the opening price to compute the trading performance; Columns (3)-(4) use the value-weighted average daily price and Columns (5)-(6) use the closing price. Our database here is collapsed at the broker/manager/stock/month level, thus we are able to add manager/stock/time fixed effects. 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. The dependent variable is our eigenvector centrality measure. T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Variable: Value-weighted trading performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Opening Price		**Average Daily Price**		**Closing Price**	
	5 Days	**10 Days**	**5 Days**	**10 Days**	**5 Days**	**10 Days**
Eig. Centrality	1.573***	2.010***	0.888***	1.334**	0.852**	1.372*
	(3.754)	(2.832)	(2.930)	(2.099)	(2.023)	(1.696)
Broker Volume	-1.363	-1.724*	-1.227*	-1.687**	-1.293*	-1.787**
	(-1.523)	(-1.852)	(-1.699)	(-2.101)	(-1.749)	(-2.076)
Average Trade Size	2.702***	2.881***	0.703***	0.991***	0.0896	0.441**
	(7.847)	(9.778)	(3.745)	(4.687)	(0.523)	(2.017)
Manager-Stock-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,623,409	17,365,029	17,621,475	17,363,402	17,620,270	17,362,802
R-squared	0.397	0.430	0.389	0.427	0.381	0.422

Table 5. Broker-Manager Relationships

This table regresses the value-weighted trading performance over five trading days (in basis points) on our centrality measures, interacted by three different proxies capturing the strength of the manager-broker relationship in each month. The first proxy is proportional to 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. Our final proxy 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. Our database here is collapsed at the broker/manager/stock/time level (where time means the five trading days window). 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 both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Variable: Value-weighted trading performance over five trading days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ranking of Manager-Broker Volume				Ranking of Revenue Share				Frequency of Manager-Broker Interaction			
Centrality × Relationship Strength	4.120***	3.779***	3.896***	3.701***	2.737*	2.706*	2.688*	2.471	0.109**	0.108**	0.109**	0.115**
	(2.812)	(2.627)	(2.663)	(2.587)	(1.772)	(1.831)	(1.812)	(1.614)	(2.012)	(1.978)	(1.999)	(2.120)
Relationship Strength	-15.18***	-15.38***	-14.61***	-12.68***	-9.034**	-9.532***	-8.893**	-7.418**	-0.0249	-0.0346	-0.0303	-0.0542
	(-4.845)	(-4.861)	(-4.718)	(-4.229)	(-2.459)	(-2.638)	(-2.505)	(-2.085)	(-0.274)	(-0.373)	(-0.330)	(-0.601)
Centrality	-2.881*	-2.643	-2.748*	-2.885*	-1.588	-1.622	-1.615	-1.738	1.129	1.072	1.059	0.767
	(-1.742)	(-1.605)	(-1.670)	(-1.837)	(-1.303)	(-1.360)	(-1.347)	(-1.442)	(1.286)	(1.228)	(1.231)	(0.864)
Broker Volume	0.151	0.00379	0.0304	-0.222	0.0753	-0.0612	-0.0369	-0.272	-0.309	-0.395	-0.412	-0.604
	(0.109)	(0.00273)	(0.0221)	(-0.180)	(0.0539)	(-0.0435)	(-0.0265)	(-0.219)	(-0.218)	(-0.277)	(-0.292)	(-0.480)
Controls	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No
Time FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Stock-Time FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Observations	34,734,096	34,452,536	34,734,035	34,511,266	34,734,096	34,452,536	34,734,035	34,511,266	34,561,431	34,280,954	34,561,371	34,337,716
R-squared	0.003	0.003	0.003	0.107	0.003	0.003	0.003	0.107	0.003	0.003	0.003	0.107

Table 6. Large Trade

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 in three sub-periods: 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 to 4). When we refer to week one after the large trade, we identify the period that ranges from end of the competition period to the end of the first week after the large trade week; in a similar way, when we refer to week two to four. 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. Panel B reports the same specification but interacting the time dummies with the centrality measure. We include as a control the natural logarithm of the dollar trade volume intermediated by each 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. T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. 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		Yes	
Manager-Time FE		Yes		Yes
Stock-Time FE	Yes	Yes	Yes	Yes
Observations	21,019,798	20,999,192	20,964,660	20,944,053
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)
Competition	0.00442	0.00155	0.0480	-0.0126
	(0.337)	(0.121)	(0.146)	(-0.0390)
Week 1	0.00147	0.00129	0.0298	0.0249
	(0.871)	(0.763)	(0.757)	(0.639)
Week 2	0.00351**	0.00344**	0.0765**	0.0756**
	(2.295)	(2.312)	(2.206)	(2.232)
Week 3	0.00422**	0.00443**	0.112***	0.117***
	(2.234)	(2.342)	(2.753)	(2.867)
Week 4	0.00621***	0.00619***	0.156***	0.157***
	(2.644)	(2.613)	(2.895)	(2.872)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes		Yes	
Manager-Time FE		Yes		Yes
Stock-Time FE	Yes	Yes	Yes	Yes
Observations	21,019,798	20,999,192	20,964,660	20,944,053
R-squared	0.079	0.093	0.077	0.092

Table 7. Unusual Stocks for Followers

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 restrict attention to stocks that have been above the median of trading volume for the originator in the previous six months and in the bottom decile for the followers. We divide the sample in three sub-periods: 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 to 4). When we refer to week one after the large trade, we identify the period that ranges from end of the competition period to the end of the first week after the large trade week; in a similar way, when we refer to week two to four. 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. Panel B reports the same specification but interacting the time dummies with the centrality measure. We include as a control the natural logarithm of the dollar trade volume intermediated by each 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. T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. 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	0.0829***	0.0784***	1.882***	1.734***
	(6.727)	(5.798)	(6.824)	(5.795)
Week 1	0.00539	0.00695	0.104	0.112
	(1.079)	(1.301)	(0.885)	(0.902)
Week 2	-0.00599	-0.00613	-0.163	-0.196
	(-1.073)	(-0.944)	(-1.222)	(-1.295)
Week 3	0.000180	-0.00176	0.000869	-0.0684
	(0.0288)	(-0.232)	(0.00614)	(-0.417)
Week 4	-0.000941	-0.00945	-0.0286	-0.249
	(-0.120)	(-0.994)	(-0.170)	(-1.276)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes		Yes	
Manager-Time FE		Yes		Yes
Stock-Time FE	Yes	Yes	Yes	Yes
Observations	280,188	263,917	279,840	263,563
R-squared	0.520	0.609	0.519	0.612

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	0.0243***	0.0226***	0.582***	0.545***
	(4.575)	(3.811)	(4.612)	(3.959)
Centrality × Week 1	0.00570	0.00237	0.137	0.0726
	(1.468)	(0.562)	(1.479)	(0.726)
Centrality × Week 2	-0.00437	-0.0107**	-0.0969	-0.224*
	(-0.929)	(-1.975)	(-0.906)	(-1.866)
Centrality × Week 3	-0.0113**	-0.0191***	-0.262**	-0.426***
	(-2.326)	(-3.445)	(-2.434)	(-3.491)
Centrality × Week 4	-0.0152**	-0.0197**	-0.310**	-0.367**
	(-2.309)	(-2.501)	(-2.244)	(-2.273)
Centrality	0.00813**	0.00776*	0.199***	0.190**
	(2.469)	(1.940)	(2.609)	(2.001)
Competition	0.0235	0.0224	0.461	0.390
	(1.483)	(1.294)	(1.268)	(0.996)
Week 1	-0.00710	0.00151	-0.195	-0.0521
	(-0.687)	(0.137)	(-0.798)	(-0.201)
Week 2	0.00329	0.0169	0.0425	0.286
	(0.283)	(1.256)	(0.159)	(0.962)
Week 3	0.0241*	0.0390***	0.557*	0.841***
	(1.863)	(2.636)	(1.938)	(2.642)
Week 4	0.0310*	0.0323	0.624*	0.530
	(1.824)	(1.569)	(1.800)	(1.319)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes		Yes	
Manager-Time FE		Yes		Yes
Stock-Time FE	Yes	Yes	Yes	Yes
Observations	280,188	263,917	279,840	263,563
R-squared	0.520	0.609	0.520	0.612

Table 8. Placebo: Shift of Timeline

This table relates the trading behavior of followers after the eight week *before* the large trade week (our *shifted week).* 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 in three sub-periods: the two trading weeks preceding the shifted week (before); the shifted week (competition); and the period up to four weeks after the shifted week (week 1 to 4). 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. We include as a control the natural logarithm of the dollar trade volume intermediated by each 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. T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)
	Dummy=1 if follower trades in the same direction as the informed trade		Log of dollar imbalances from followers	
Competition	-0.000285	-0.000177	-0.00887	-0.00646
	(-0.494)	(-0.304)	(-0.712)	(-0.515)
Week 1	-0.000550	-0.000425	-0.0118	-0.00899
	(-0.576)	(-0.455)	(-0.565)	(-0.438)
Week 2	0.000378	0.000398	0.00755	0.00766
	(0.399)	(0.432)	(0.355)	(0.371)
Week 3	7.18e-05	-5.20e-05	0.000200	-0.00277
	(0.0783)	(-0.0574)	(0.0103)	(-0.145)
Week 4	0.000123	0.000132	0.00397	0.00322
	(0.101)	(0.111)	(0.154)	(0.128)
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes		Yes	
Manager-Time FE		Yes		Yes
Stock-Time FE	Yes	Yes	Yes	Yes
Observations	22,271,277	22,251,239	22,214,272	22,194,225
R-squared	0.071	0.084	0.069	0.082

Table 9. Who Follows the Informed Trade?

Panel A regresses the delay after the large trade on a dummy that identifies an affiliation relationship between the broker who intermediated the large trade and the manager who acts as a follower. We consider an asset manager affiliated to a broker, whenever the broker and the manager belong to the same firm or holding company. Panel B regresses the delay after the large trade on our measure of eigenvector centrality, interacted by our proxies for strength of manager-broker relationship. The delay is defined as the time passing from the large trade up to the first time other managers (followers) trade the stock with the same broker who intermediated the large trade; time is measured in minutes. A large trade is identified by a broker who intermediated the trade, a manager who generated the trade, the stock involved in the trade and the week in which the trade occurred. For each trade we keep track of all the managers who, after the large trade, trade again the stock with the same broker. We include as a control the natural logarithm of the dollar trade volume intermediated by each broker in the last six months and the natural logarithm of the large trade volume, taken in absolute value (scaled by the trading volume in CRSP). T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Affiliation

	Dependent Variable: Delay after the large trade					
	(1)	(2)	(3)	(4)	(5)	(6)
Affiliated	-5,079***	-5,120***	-5,697***	-5,297***	-5,321***	-5,845***
	(-11.60)	(-11.69)	(-13.92)	(-11.94)	(-11.84)	(-13.49)
Broker Volume	-102.4	-151.7	-529.9**	-1,390***	-1,240***	-1,132***
	(-0.455)	(-0.641)	(-2.214)	(-6.854)	(-6.172)	(-5.820)
Large trade volume	-210.5***	-202.2***	-80.04*	-152.9***	-154.8***	-85.75**
	(-4.111)	(-5.381)	(-1.747)	(-3.968)	(-5.235)	(-2.394)
Time FE	Yes	Yes	No	Yes	Yes	No
Stock FE	Yes	Yes	No	Yes	Yes	No
Manager FE	No	Yes	No	No	Yes	No
Stock-Time FE	No	No	Yes	No	No	Yes
Manager-Time FE	No	No	Yes	No	No	Yes
Broker FE	No	No	No	Yes	Yes	Yes
Observations	4,852,004	4,852,004	4,709,827	4,852,004	4,852,004	4,709,827
R-squared	0.027	0.031	0.267	0.036	0.038	0.269

Panel B: Relationships

Dependent Variable: Delay after the large trade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ranking of Manager-Broker Volume			**Revenue Share**			**Frequency of Manager-Broker Interaction**		
Centrality × Relationship Strength	-1,138***	-1,039***	-430.5**	-1,405***	-1,028***	-473.9***	-26.77***	-20.06***	-9.388**
	(-3.307)	(-2.768)	(-2.281)	(-4.003)	(-3.313)	(-2.823)	(-3.554)	(-3.053)	(-2.051)
Centrality	793.6***	665.6***	379.1**	1,016***	643.2***	409.9***	-381.6**	-295.8*	-41.22
	(3.374)	(2.824)	(2.373)	(3.594)	(3.053)	(2.812)	(-2.370)	(-1.763)	(-0.756)
Relationship Strength	2,251***	1,622	1,246***	3,627***	2,139**	1,574***	76.38***	41.92**	20.70*
	(3.072)	(1.648)	(2.793)	(3.998)	(2.410)	(3.627)	(3.634)	(2.575)	(1.952)
Large trade volume	-164.8***	-114.9**	-116.8***	-166.0***	-115.3**	-116.7***	-156.6***	-165.6***	-117.4***
	(-3.955)	(-2.379)	(-3.119)	(-3.973)	(-2.380)	(-3.094)	(-3.190)	(-3.906)	(-3.129)
Broker Volume	-161.2	-245.3	-1,137***	-177.1	-251.5	-1,137***	-99.45	-135.5	-1,137***
	(-0.801)	(-1.073)	(-5.185)	(-0.907)	(-1.104)	(-5.188)	(-0.503)	(-0.618)	(-5.162)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	No	No	Yes	No	No	Yes	No	No
Manager-Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Broker FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	4,713,706	4,712,731	4,712,731	4,713,706	4,712,731	4,712,731	4,672,193	4,672,193	4,671,225
R-squared	0.032	0.051	0.054	0.033	0.051	0.054	0.029	0.032	0.053

Table 10. News Events

Dollar trade imbalances around earnings announcement dates regressed on Broker Centrality interacted by a dummy identifying a positive earnings surprise, i.e. realized earnings above analyst's consensus. The sample is split based on the managers' performance on the stock in the previous six months. We include as a control the dollar trade volume intermediated by each broker in the last six months. Panel A shows the results considering all managers. Panel B only includes the managers who lie in the top quartile of trade performance for the stock in the previous six months. T-stats based on robust standard errors, clustered at the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: All Institutional Investors

Dependent Variable: Dollar trade imbalances around earnings announcement dates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	10 days before the announcement				**Announcement day**				**10 days after the announcement**			
Centrality × Positive Surprise	7,199	6,533	5,806	8,687	4,323	3,837	18,020	18,417	17,261**	17,293**	24,667***	26,131***
	(0.794)	(0.772)	(0.677)	(1.068)	(0.635)	(0.562)	(1.350)	(1.366)	(2.246)	(2.238)	(2.824)	(2.997)
Eig. Centrality	1,214	894.6	17,294	1,226	-12,958	-13,483	-13,959	-26,302*	492.0	-296.2	7,184	-4,480
	(0.146)	(0.0931)	(0.926)	(0.107)	(-1.594)	(-1.528)	(-0.811)	(-1.838)	(0.0433)	(-0.0239)	(0.373)	(-0.322)
Positive Surprise	-23,705*	-15,997		9.868e+12	15,178	25,712		9.441e+11	22,512	21,731		2.333e+12
	(-1.697)	(-1.021)		(0.00238)	(0.608)	(0.995)		(0.000804)	(1.111)	(1.070)		(0.000785)
Broker Volume	-0.0444	-0.0564	-0.0526	0.00164	-0.0851	-0.101	-0.129	-0.102	0.0363	0.0138	0.107	0.0631
	(-0.431)	(-0.528)	(-0.471)	(0.0130)	(-0.583)	(-0.679)	(-0.949)	(-0.642)	(0.436)	(0.162)	(1.230)	(0.654)
Manager FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Stock FE	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No
Event FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,365,542	4,365,345	4,357,683	4,357,668	927,555	927,158	902,979	902,941	4,992,702	4,992,509	4,985,490	4,985,476
R-squared	0.001	0.001	0.019	0.020	0.001	0.003	0.054	0.055	0.000	0.001	0.020	0.021

Panel B: Only Top Performing Managers

Dependent Variable: Dollar trade imbalances around earnings announcement dates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	10 days before the announcement				**Announcement day**				**10 days after the announcement**			
Centrality × Positive Surprise	17,655*	17,900*	25,656**	25,648**	-1,850	-5,176	10,165	8,133	27,156***	28,167***	18,664	18,884
	(1.658)	(1.867)	(2.163)	(2.157)	(-0.166)	(-0.406)	(0.600)	(0.473)	(3.686)	(3.579)	(1.070)	(1.098)
Eigenvector Centrality	749.3	-99.57	23,977	2,637	3,232	4,374	8,407	-6,857	-709.0	-3,010	26,770	7,919
	(0.0395)	(-0.00449)	(0.672)	(0.0789)	(0.454)	(0.576)	(0.814)	(-0.631)	(-0.0573)	(-0.223)	(1.278)	(0.445)
Positive Surprise	-54,087**	-59,114**		3.028e+09	-40,445	-38,770		-1.758e+09	-46,108*	-57,866**		-4.667e+10
	(-2.537)	(-2.555)		(1.98e-05)	(-1.136)	(-1.061)		(-4.67e-06)	(-1.690)	(-2.035)		(-5.57e-05)
Broker Volume	0.122	0.0964	0.174	0.170	-0.0669	-0.106	0.0876	-0.0391	0.00408	-0.0186	0.113	0.0401
	(0.607)	(0.457)	(0.878)	(0.757)	(-0.280)	(-0.451)	(0.367)	(-0.149)	(0.0326)	(-0.139)	(0.728)	(0.239)
Manager FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Stock FE	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No
Event FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,003,970	1,003,572	982,181	982,119	219,066	218,466	188,185	188,101	1,169,679	1,169,277	1,148,724	1,148,681
R-squared	0.002	0.004	0.068	0.070	0.002	0.011	0.165	0.168	0.001	0.003	0.111	0.112

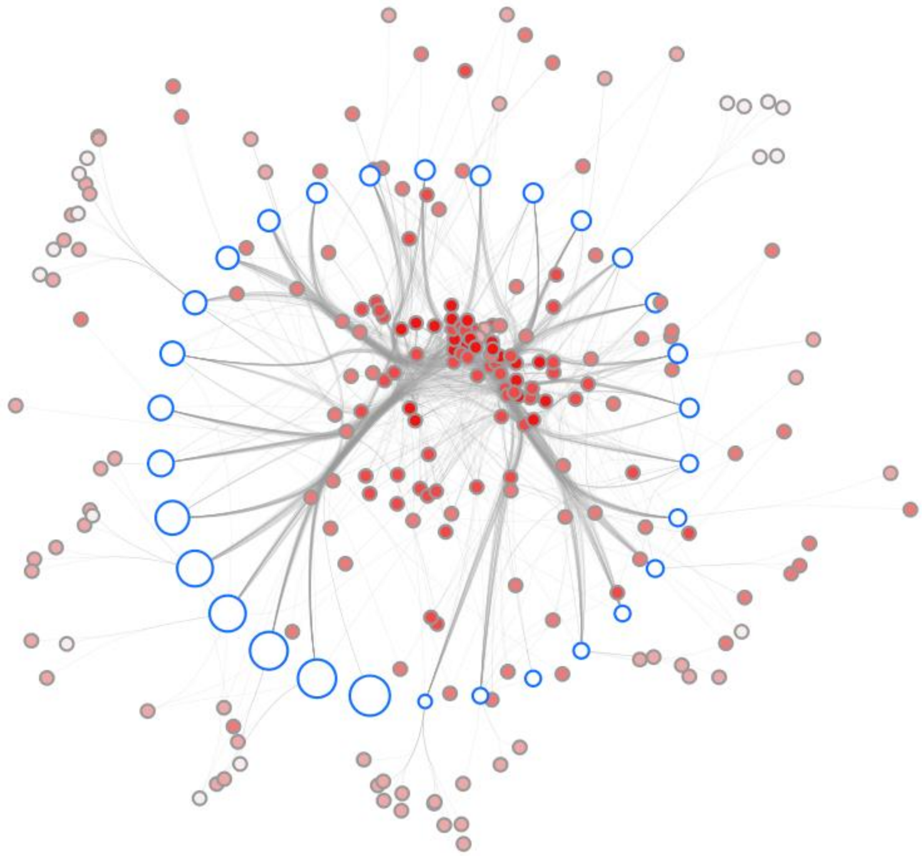

Figure 1

This figure depicts the network of managers (*grey* 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 grey) up to a very high volume (in intense *red* – or an intense grey).

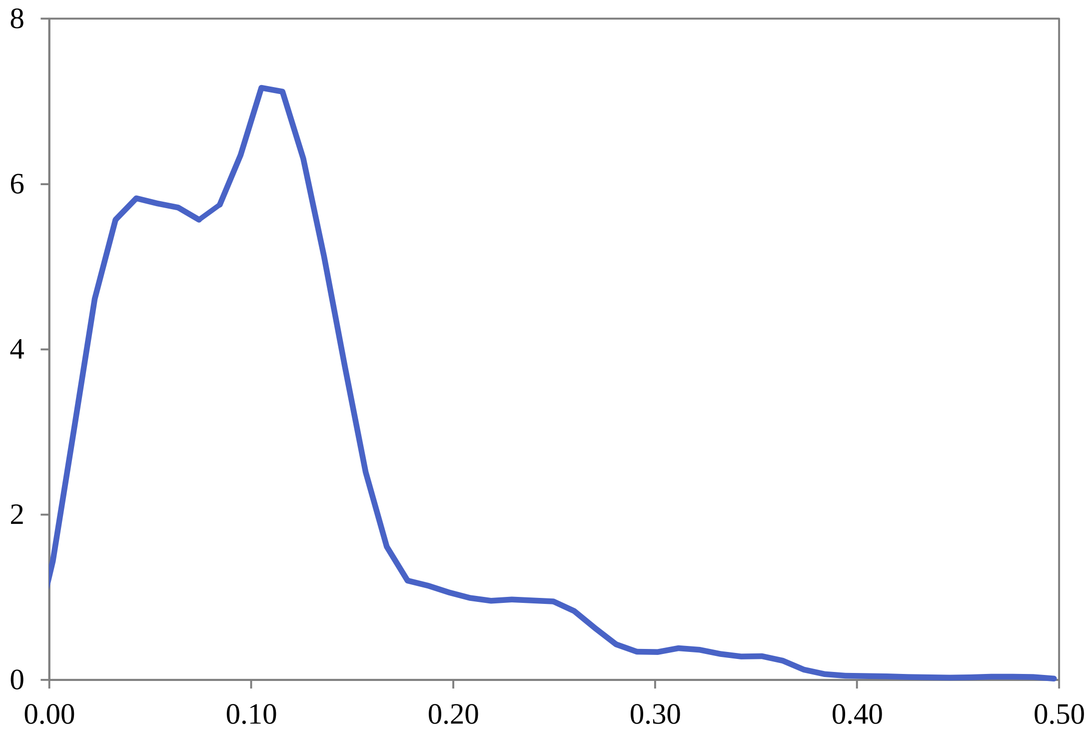

Figure 2

Kernel density estimation of eigenvector centrality over the whole time sample, i.e. July 1999 – December 2014.

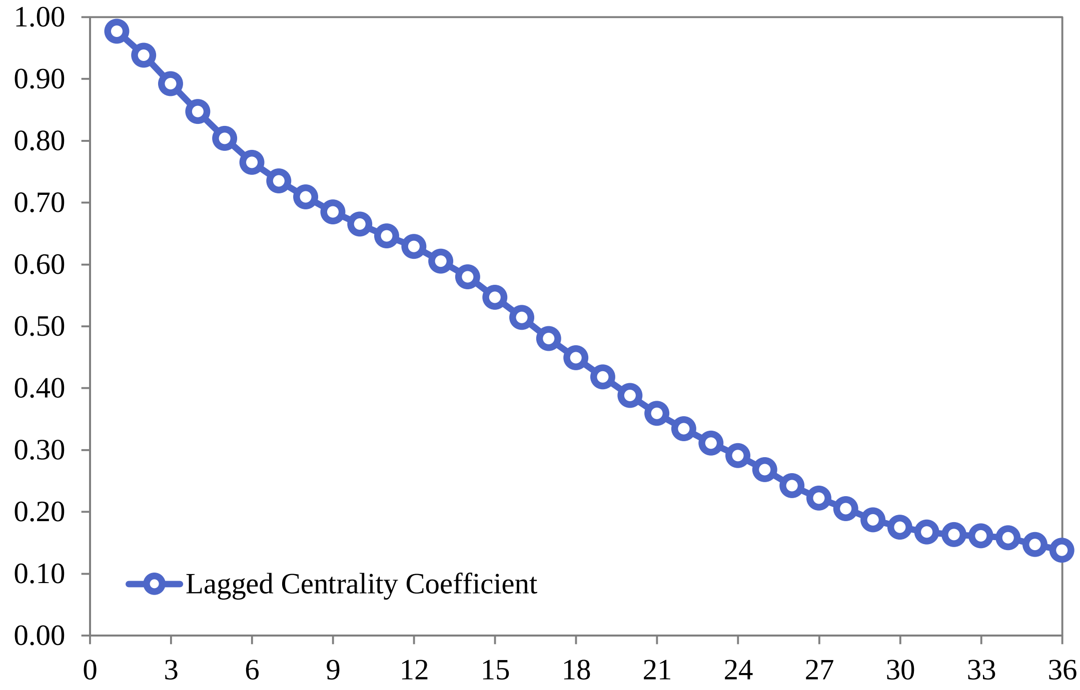

Figure 3

Eigenvector Centrality regressed on its lags, one at the time, starting from one month and moving up to 36 months.

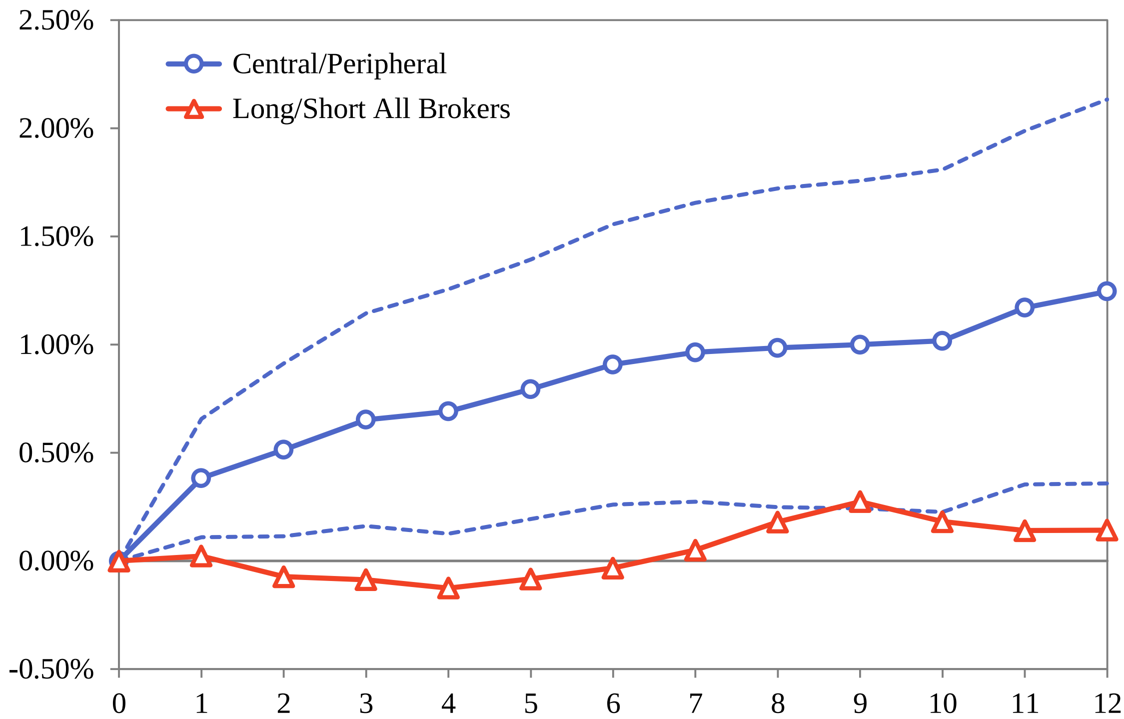

Figure 4

Cumulative return of the *high-minus-low centrality* portfolio built on month zero over the following twelve months (without rebalancing every three months), with a 95% confidence interval (in *blue* – marked by the circles), together with the cumulative return of a generic long/short portfolio built on month zero (in *red* – marked by triangles) by looking at the imbalances passing through the brokers, but without discriminating between central and peripheral brokers.

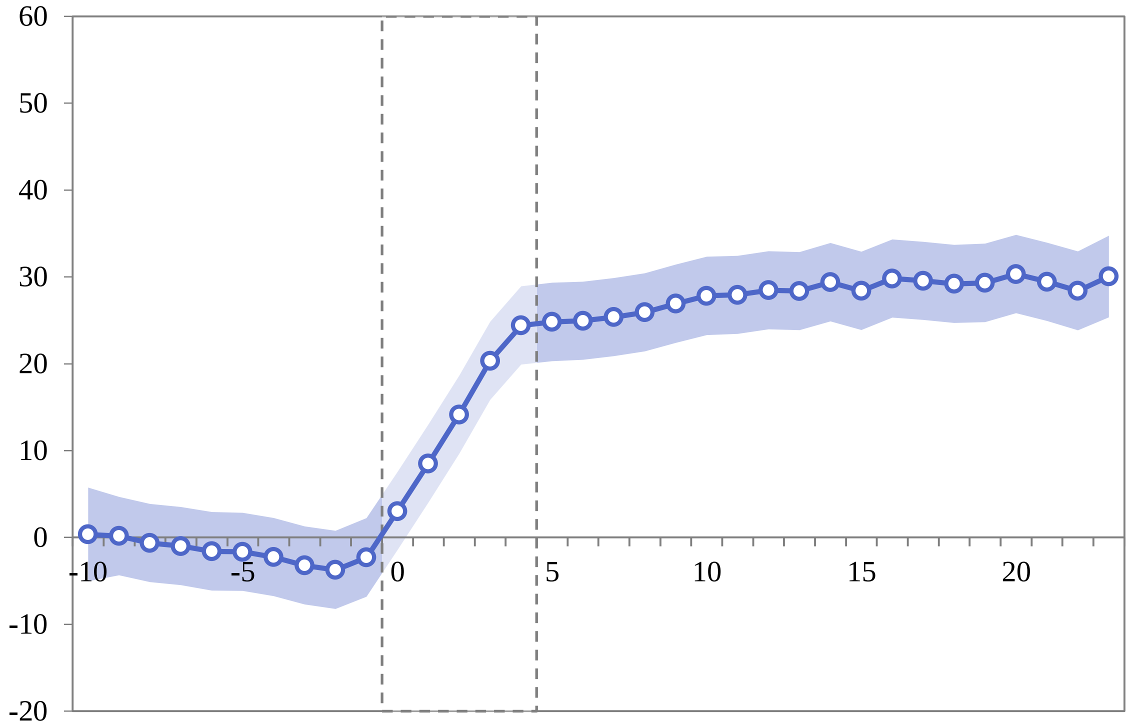

Figure 5

Cumulative abnormal returns of the stock interested by a large trade before, during and after the week in which the large trade is identified (starting on day zero and ending on day four).

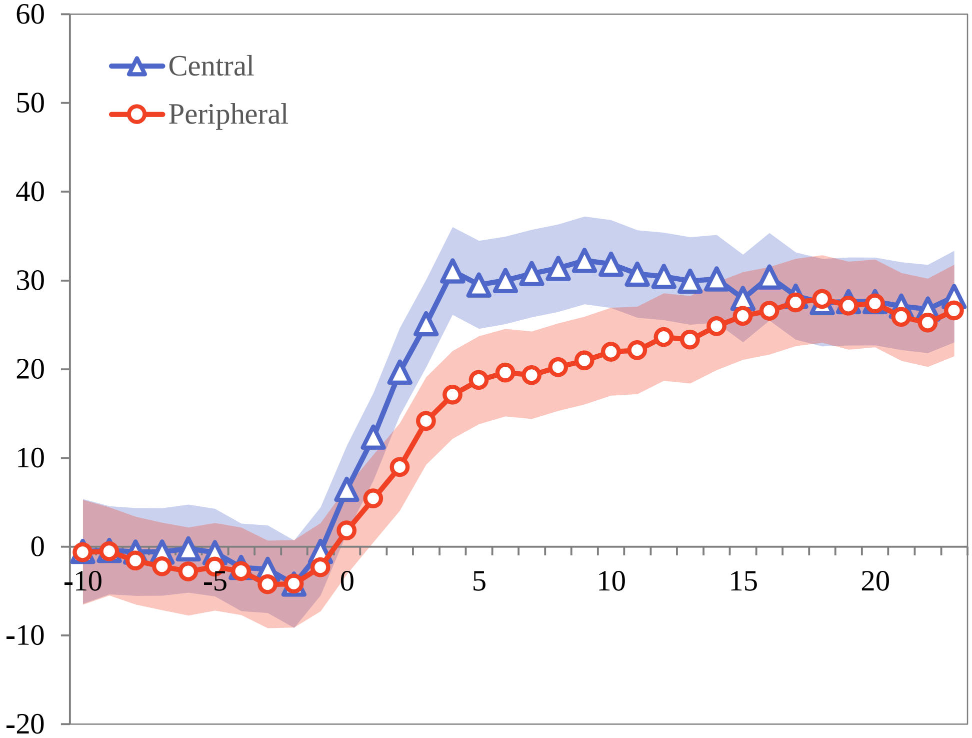

Figure 6

Cumulative abnormal returns of the stock interested by a large trade before, during and after the week in which the large trade is identified (starting on day zero and ending on day four). We separate between large trades intermediated by central broker (in *blue* – marked by the triangles) and peripheral brokers (in *red* – marked by the circles). *Central broker* here means all the brokers whose eigenvector centrality lies above the 60^{th} percentile of its distribution. The areas in blue and red are the standard errors: whenever they are not overlapping, it means that the difference between the central broker line and the peripheral broker line is significant at the 5% level.

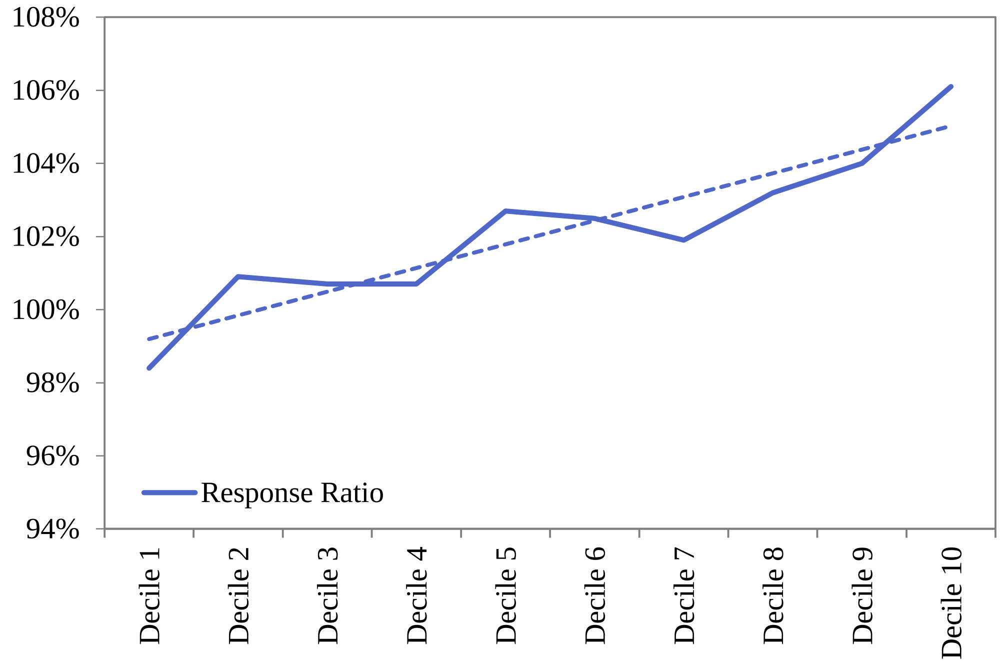

Figure 7

This figure plots the coefficients of a regression relating the ratio between the cumulative Fama-French 4 factor returns on day 5 and day 25 on the deciles of eigenvector centrality.

7. Online Appendix

Table A.1 Returns and Broker Volume

This table regress the value-weighted trading performance net of fees and commissions paid to the broker at different time horizons (in basis points) on our centrality measures. 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. T-stats based on robust standard errors, double clustered at both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Variable: Value-weighted trading performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1 Day			**5 Days**			**10 Days**		
Eig. Centrality	0.973***	0.693***	0.581***	1.738***	1.254***	1.134***	2.121***	1.425***	1.576***
	(6.276)	(4.540)	(4.109)	(4.594)	(3.299)	(2.987)	(4.007)	(2.668)	(2.931)
Broker Volume	0.616***	0.863***	1.113***	0.889*	1.607***	2.145***	0.926	1.880***	2.483***
	(3.471)	(5.006)	(6.597)	(1.840)	(3.390)	(4.515)	(1.618)	(3.313)	(4.267)
Average Trade Size	-0.660***	-1.204***	-1.798***	-2.346***	-3.455***	-4.383***	-2.848***	-3.891***	-4.777***
	(-4.687)	(-8.810)	(-11.61)	(-8.233)	(-11.26)	(-12.11)	(-6.553)	(-7.852)	(-9.508)
Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Mgr FE	No	Yes	No	No	Yes	No	No	Yes	No
Mgr/Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	633,603	633,591	624,100	629,936	629,925	620,431	622,216	622,204	612,733
R-squared	0.003	0.012	0.130	0.002	0.006	0.131	0.001	0.005	0.137

Table A.2 Broker-Manager Relationships

This table regresses the value-weighted trading performance over five trading days (in basis points) on our centrality measures, interacted by three different proxies capturing the strength of the manager-broker relationship in each month. The first proxy is proportional to 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. Our final proxy 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. We regress the value-weighted trading performance at different time horizons (in basis points) regressed on our eigenvector centrality measure, interacted by dummies indicating quartiles of strength for the manager-broker relationship, as captured by our three proxies. Our database here is collapsed at the broker/manager/stock/time level (where time means the five trading days window). 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 both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Variable: Value-weighted trading performance over five trading days									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ranking of Manager-Broker Volume			**Revenue Share**			**Frequency of Manager-Broker Interaction**		
Centrality × First Quartile Relationship Strength	0.598	0.112	0.642	0.495	0.00729	0.541	2.668**	1.813	2.136*
	(0.599)	(0.111)	(0.613)	(0.531)	(0.00773)	(0.564)	(2.240)	(1.517)	(1.765)
Centrality × Second Quartile Relationship Strength	1.615**	1.214	1.326*	1.942***	1.433**	1.258*	0.477	0.112	0.209
	(2.239)	(1.649)	(1.731)	(2.995)	(2.165)	(1.787)	(0.605)	(0.141)	(0.250)
Centrality × Third Quartile Relationship Strength	2.327***	1.878***	1.662***	2.409***	1.991***	2.044***	2.739***	2.365***	2.349***
	(3.950)	(3.211)	(2.706)	(3.952)	(3.284)	(3.316)	(4.550)	(3.883)	(3.789)
Centrality × Fourth Quartile Relationship Strength	2.370***	2.071***	1.871***	2.204***	1.945***	1.648***	2.155***	1.793***	1.553***
	(4.279)	(3.811)	(3.429)	(4.101)	(3.703)	(3.130)	(4.107)	(3.507)	(3.130)
First Quartile Relationship Strength	-6.975***	-6.621***	-6.077**	-6.245***	-5.347**	-4.348*	-9.766***	-7.973***	-8.934***
	(-2.773)	(-2.603)	(-2.279)	(-2.792)	(-2.351)	(-1.850)	(-3.723)	(-3.056)	(-3.145)
Second Quartile Relationship Strength	-3.561	-4.273*	-3.847	-4.891**	-5.354**	-4.387	-2.711	-3.294	-3.132
	(-1.528)	(-1.826)	(-1.443)	(-2.153)	(-2.343)	(-1.622)	(-1.298)	(-1.600)	(-1.315)
Third Quartile Relationship Strength	-4.582**	-5.427***	-4.753*	-4.590**	-5.964***	-6.149***	-5.824***	-7.804***	-8.285***
	(-2.250)	(-2.680)	(-1.971)	(-2.215)	(-2.904)	(-2.622)	(-3.051)	(-4.162)	(-4.150)
Fourth Quartile Relationship Strength	-0.0241	-3.432	-2.839	0.264	-3.052	-3.248	-1.155	-4.574**	-4.814**
	(-0.0108)	(-1.569)	(-1.109)	(0.117)	(-1.373)	(-1.250)	(-0.621)	(-2.526)	(-2.392)
Broker Volume	3.49e-06	2.38e-05*	3.97e-05***	2.90e-06	2.31e-05*	3.93e-05***	-8.21e-06	1.87e-05	3.70e-05***
	(0.270)	(1.931)	(3.236)	(0.226)	(1.879)	(3.207)	(-0.645)	(1.562)	(3.104)
Trade Volume	-4.233***	-4.831***	-5.766***	-4.146***	-4.777***	-5.657***	-3.691***	-4.539***	-5.575***
	(-11.68)	(-13.37)	(-13.80)	(-11.90)	(-13.48)	(-13.81)	(-11.89)	(-13.67)	(-14.23)
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	629,936	629,925	620,437	629,936	629,925	620,437	629,936	629,925	620,437
R-squared	0.002	0.006	0.131	0.002	0.006	0.131	0.002	0.006	0.131

Table A.3 Large Trade Profits

This table relates the probability of a positive return over five trading days (the dependent variable) for a manager (who is required to be an Hedge Fund) executing a large net volume with a specific broker on a stock, with respect to non-large net volume executions. Large net volumes over a five trading days window are captured by the dummy variable Large Trade and are defined as net volumes (i.e. imbalances) larger or equal than the 75th percentile (or the 90th percentile) of the imbalances distribution estimated in the previous six months. All the imbalances are scaled by the trading volume in CRSP. We include as a control the natural logarithm of the market capitalization and the Amihud illiquidity measure for the stock, estimated over the previous twelve months. T-stats are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Variable: Dummy that identifies positive profits

	(1)	(2)	(3)	(4)
	P75		**P90**	
Large Trade	0.503***	0.505***	0.690***	0.691***
	(218.3)	(219.5)	(146.5)	(147.1)
Market Cap	0.00912***		0.0104***	
	(26.07)		(29.92)	
Amihud Illiquidity	-0.408***		-0.446***	
	(-7.013)		(-7.797)	
Constant	2.026***	2.228***	2.032***	2.264***
	(259.8)	(3,489)	(261.3)	(3,674)
Observations	34,950,742	35,236,163	34,950,742	35,236,163

Table A.4 Unusual Stocks

The table reports coefficient estimates of least square regressions relating the value-weighted trading performance at different time horizons (in basis points) and our centrality measures. Our database here is collapsed at the broker/manager/stock/month level, thus we are able to add stock and stock/time fixed effects. In these test we interact our centrality measure with a dummy (unusual) that flags the stocks we deem as unusual for the broker. We compute for each stock/broker pair the dollar volume in the stock intermediated by the broker in the previous six months, as a percentage of the total dollar volume intermediated by the broker. We then adjust this to take into account the total number of stocks traded by the broker in the same period. Finally, we consider as unusual stocks for a broker all the stocks whose adjusted percentage volume lies below the tenth percentile of its distribution across all stocks/months in our sample. 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 both the month and the manager level, are reported in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable: Value-weighted trading performance

	(1)	(2)	(3)	(4)	(5)	(6)
	1 Days		**5 Days**		**10 Days**	
Centrality × Unusual	0.515**	0.415*	1.904**	1.695*	2.995**	2.825**
	(2.015)	(1.854)	(2.119)	(1.910)	(2.525)	(2.404)
Unusual Stocks	-0.653	-0.433	-4.692*	-4.325*	-7.741**	-7.010**
	(-0.745)	(-0.571)	(-1.968)	(-1.915)	(-2.205)	(-2.100)
Centrality	0.457**	0.236	1.009***	0.716**	1.149	0.622
	(2.316)	(1.224)	(2.711)	(2.277)	(1.601)	(1.398)
Broker Volume	-0.213	-0.218	-0.998*	-1.255**	-1.584*	-1.830**
	(-1.110)	(-1.327)	(-1.683)	(-2.129)	(-1.930)	(-2.319)
Average Trade Volume	0.310***	0.126	0.438*	0.0932	0.704**	0.419
	(3.030)	(1.297)	(1.960)	(0.386)	(1.989)	(1.224)
Manager FE	No	Yes	No	Yes	No	Yes
Stock-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,472,436	22,472,433	22,339,563	22,339,561	22,071,583	22,071,580
R-squared	0.039	0.040	0.044	0.045	0.049	0.050