9-2021

Inside brokers

Frank Weikai LI
Singapore Management University, wkli@smu.edu.sg

Abhiroop MUKHERJEE
Hong Kong University of Science and Technology

Rik SEN
University of New South Wales

Inside Brokers

Frank Weikai Li, Abhiroop Mukherjee, and Rik Sen

September 2020*

Abstract

We identify the broker each corporate insider trades through and show that analysts and mutual fund managers affiliated with such "inside brokers" retain a substantial information advantage on the insider's firm, even after these trades are disclosed. Affiliated analysts issue more accurate earnings forecasts, and affiliated mutual funds trade the insider's stock more profitably than their peers, following insider trades through their brokerage. Our results challenge the prevalent perception that information asymmetry arising from insider trading is acute only before trade disclosure and suggest that brokers facilitating these trades are in a position to exploit this asymmetry.

JEL classification: G24, G30, G34, G38

Keywords: Analysts, Mutual Funds, Insiders, Brokers, Information Transmission

*Li: Singapore Management University; Mukherjee: Hong Kong University of Science and Technology; Sen: University of New South Wales. We are grateful to an anonymous referee for many helpful suggestions, and to Renee Adams, Sumit Agarwal, Vikas Agarwal, Nicholas Barberis, Brad Barber, Utpal Bhattacharya, Justin Birru, Kalok Chan, Vidhi Chhaochharia, Darwin Choi, Lauren Cohen, Henrik Cronqvist, Sudipto Dasgupta, Qianqian Du, Vyacheslav Fos, Francesco Franzoni, Mark Grinblatt, Allaudeen Hameed, Harrison Hong, Wenxuan Hou, Yawen Jiao, Marcin Kacperczyk, Egle Karmaziene, Alok Kumar, George Korniotis, Sun Lei, Roger Loh, Dong Lou, Christopher Malloy, Gustavo Manso, Ron Masulis, Kasper Nielsen, Wenlan Qian, David Reeb, Tao Shu, Noah Stoffman, Laura Starks, Prasanna Tantri, Sheridan Titman, Baolian Wang, Chishen Wei, John Wei, Tong Yao, and David Yermack as well as conference/seminar audiences at the AFA, the ABFER, the CICF, the EFA, FIRS, Financial Research Workshop at IIMC, ISB Summer Research Conference, Lithuanian Conference on Economic Research, Tel Aviv University Finance Conference, CUHK, CUHK Shenzhen, HKUST, Humboldt University, Indian School of Business, Korea University Business School, LMU Munich, NTU Singapore, University of Georgia, University of Lancaster, University of Miami, UNSW, University of Technology Sydney and the University of Queensland for useful comments. Mukherjee gratefully acknowledges financial support from the General Research Fund of the Research Grants Council of Hong Kong (Project Number: 692313). Li also thanks Princeton University for hosting him for a part of the time during which this research was conducted.

Inside Brokers

September 2020

Abstract

We identify the broker each corporate insider trades through and show that analysts and mutual fund managers affiliated with such "inside brokers" retain a substantial information advantage on the insider's firm, even after these trades are disclosed. Affiliated analysts issue more accurate earnings forecasts, and affiliated mutual funds trade the insider's stock more profitably than their peers, following insider trades through their brokerage. Our results challenge the prevalent perception that information asymmetry arising from insider trading is acute only before trade disclosure and suggest that brokers facilitating these trades are in a position to exploit this asymmetry.

JEL classification: G24, G30, G34, G38

Keywords: Analysts, Mutual Funds, Insiders, Brokers, Information Transmission

1 Introduction

When corporate insiders trade, can intermediaries facilitating the trade – such as stockbrokers – gain any long-lived information advantage in the process? These brokers know who is trading and how much they traded before the trade is publicly disclosed, so it is well understood that they have an early advantage. But this type of advantage lasts only until trade disclosure, which is typically within two days of trading, after which all market participants are presumed to be on an equal footing. In this paper, we show that the brokers' information advantage is more pervasive than previously believed: it is substantial and long-lived, lasting well beyond mandatory trade disclosure. Our evidence focuses on analysts and mutual funds affiliated with brokers through whom insiders trade and suggests that they benefit from an economically significant "inside broker" advantage that lasts well beyond the pre-disclosure period.

Where could such a long-lived information advantage come from? One possibility is that the insider's broker knows the exact nature/timing of the trading instruction (e.g., whether it was a limit order placed long in advance, or a quick market order placed right after a board meeting), which the rest of the market will not find out even after the trade is disclosed to the U.S. Securities and Exchange Commission (SEC). Or there could be other means, like the broker's interactions with the insider in the trading process, that could facilitate better inference regarding the extent of information associated with a trade. For example, the broker might know that a large sale by an insider is actually liquidity motivated (e.g., it is the first trade in a regular and uninformed trading sequence), but the market may incorrectly believe it is informative about future firm prospects. In this case, the broker's information advantage is in knowing that the trade is uninformative.

We find two related yet distinct reflections of such an "inside broker" advantage. First, we find that the equity analyst who covers the insider's firm at the insider's brokerage issues earnings forecasts that are 10.5% more accurate after the insider has traded through her brokerage. Second, we find that mutual funds affiliated with such inside brokers (e.g., "Wells Fargo Small Cap Fund" is affiliated with Wells Fargo's brokerage) also enjoy a significant information advantage when they trade the insider's company shares. Following affiliated fund trades leads to 89 basis points higher returns on the insider's stock over the following quarter. Importantly, these affiliated analysts' forecasts are issued – and fund managers' holdings are disclosed – well after the occurrence of the insider trade itself becomes public through SEC filings. Our evidence therefore suggests that the inside broker retains a substantial information advantage beyond trade disclosure.

The key to our study is the identity of the insiders' brokers. We identify these brokers through SEC's Form 144, through which insiders are required to report the broker used for sales of restricted and control shares. We hand-match these brokerage names to the I/B/E/S dataset to identify affiliated analysts, and separately to CRSP/Thomson Reuters mutual fund names to ascertain broker-affiliated mutual funds. Our goal, then, is to estimate the effect of an insider's trade on the information advantage enjoyed by these affiliated analysts and fund managers.

To get a causal estimate of such an effect, the ideal experiment would be to allow every insider to pick more than one – say, two – brokers with whom he could have a long-term relationship. Then, each time the insider wishes to trade, the experimenter would randomly pick one of these two brokers to execute that trade. One could then measure the information advantage of the broker selected for that trade, by comparing with the other broker – who was also picked by the insider but did not facilitate this trade. We do not have such a setting in the real world, where insiders typically do not have multiple personal brokers at any given point in time. We therefore lack an ideal control broker for each insider trade. Fortunately, however, we can exploit the granularity of panel data available – both for analysts and for mutual funds – to overcome most associated problems of inference.

Such granularity helps in identification by allowing us to use three sets of high-dimensional fixed effects and conduct a variety of falsification tests to rule out unobserved heterogeneity. For example, in our tests using analyst forecasts, we can add fixed effects for every firm-time pair, broker-analyst-firm combination, and broker-analyst-time combination. The firm-time fixed effects control for the forecast accuracy of all analysts covering the firm at the same time. This accounts for the possibility that all analysts are able to make better forecasts after observing an insider trade, among others. Broker-analyst-firm fixed effects ensure that our effect comes from the accuracy of a specific analyst relative to her own forecasts on the same firm made in other periods while working at the same brokerage. This accounts for firm-specific analyst skill, or school ties between analysts and insiders, etc. Broker-analyst-time fixed effects help control for time-varying analyst or brokerage level unobservables, such as time-varying analyst accuracy, industry/sector experience, etc.

The simultaneous use of these high-dimensional fixed effects (HDFEs) makes our framework equivalent to estimating a triple difference, given how these fixed effects compound on one another (e.g., Imbens and Wooldridge, 2007). In particular, our estimated effect comes from comparing the relative accuracy of the connected analyst on the insider's stock following the insider trade, to other periods without any such trade. This relative accuracy is estimated taking into account any potential improvement in the accuracy of other analysts covering that same stock during the same period, and further, any general improvement in the connected analyst's accuracy on other stocks she covers at that time.

Further, using mutual funds' stock holdings data and a similar HDFE structure, we show that following affiliated mutual fund trades in the insider's stock is more profitable in the quarter after the insider trade than in other periods. Again, this relatively higher profitability is after taking into account any potential change in the profitability of following other funds' trading in that same stock at the same time, and further, any general change in the profitability of following the affiliated fund's trades on other stocks at that time. Our results therefore paint the same picture across two distinct samples – analyst forecasts and fund trades – which attests to a robust pattern. The only common feature shared by the firm-analyst pairs and the firm-fund manager pairs across these two samples is the brokerage affiliation, which suggests that this is where the information advantage comes from. Our results in these two datasets are indeed distinct – e.g., broker-affiliated fund results obtain even in the sample without analysts (e.g., Fidelity has funds but no sell-side analysts).

We follow up both sets of results on analysts and funds with a series of falsification tests designed to rule out alternative explanations. These explanations include the possibility of time-varying personal relationships, or time-varying unobserved business ties between the insiders' firm and the brokerage (e.g., investment banking relationships). Specifically, we consider breaks in the analyst/fund manager-firm connection due to (1) insiders changing brokers, (2) insiders changing jobs, and (3) analysts/fund managers changing jobs. These sever the link required for our story but are unlikely to affect other (unobserved) ties or personal relationships. In each case, we follow the analyst's/fund manager's performance in the period right after the connection breaks. None of our earlier results hold.

Next, we design further tests exploiting the fact that different insiders do not share their personal brokers in 90.3% of our sample firms. For example, we conduct a test where we compare inside brokers through whom a firm insider trades in a particular period (and is therefore likely to have an information advantage), with brokers who also have insider clients at the same firm but whose clients did not trade at the same time. We continue to find evidence similar to our baseline. Moreover, if the effect we document is indeed driven by the insider trade, we might expect it to vary over time. Consistent with this, we find that the effect of the inside-broker affiliation on analyst forecast accuracy and mutual fund trade profitability is insignificant before insider trades (similar to insignificant "pre-trends"), highest right after, and then declines with time if there are no further trades through this broker. Further, we find that the inside broker's information advantage is greater for firms whose stocks trade in a worse information environment, particularly following larger and less frequent insider trades.

Finally, we return to potential mechanisms underlying our result and examine a specific but clean context in which we are able to demonstrate the precise nature of the inside broker's information advantage. To understand our test design here, note that the information advantage we have in mind has to exist beyond the public disclosure of the trade itself. At the same time, we as econometricians must be able to demonstrate its existence from data observable to us, that is, from (ex-post) publicly available data.

One such candidate is first-in-a-regular-sequence trades by insiders. Suppose an insider sells restricted stock every January. As Cohen, Malloy, and Pomorski (2012) show, these regular trades are less likely to be information-driven. We conjecture that after observing the same insider trading in the same month over a few (say, two or three) consecutive years, all market participants will realize that such trades are part of a regular sequence and hence are not information-driven. However, when the insider trades in January for the first time, the typical outsider would not be able to foresee that this is going to be a regular and therefore uninformative trade. The affiliated analyst and fund manager, though, might know this if the information gets conveyed to the insider's broker. So the inside broker's relative information advantage is likely to be strongest for the first-in-sequence trades and then to weaken as the next-in-sequence trades start coming in. This is exactly what we observe in the data, again, both with the relative accuracy of affiliated analysts and the relative trading profitability of mutual funds – the inside-broker advantage monotonically declines from first-in-a-sequence to third-or-further-in-a-sequence trades.

One might wonder why the inside broker communicates her information to the analyst. Sell-side analysts exist mainly to help generate more business for the brokerage (e.g., Chung and Cho, 2005). More accurate forecasts by the analyst would help the broker tout the higher quality of the brokerage's in-house research and generate more business from clients in the future. One might also wonder if such communication breaches a "Chinese Wall." It does not necessarily. Since both the broker and the analyst work in the brokerage division, and the nature of the brokerage business requires them to work in close collaboration and interact with each other, there cannot be a Chinese Wall between them. On the other hand, the interaction between the broker and the affiliated fund manager likely does breach a Chinese Wall, since they work in two different divisions of the financial conglomerate. Here, we add to the evidence on the flow of information across divisions of financial conglomerates that has been shown in other contexts. For example, Massa and Rehman (2008) show that mutual funds increase their holdings in firms that borrow from affiliated commercial banks and are able to deliver better performance on these holdings, presumably due to an information advantage. Chen and Martin (2011) show that private information from lending activities improves the forecast accuracy of bank-affiliated analysts.

In the context of the brokerage itself, MacNally, Shkilko, and Smith (2017) show that when an insider trades through a brokerage in Canada, the brokerage's other clients trade in the same direction on that day. Geczy and Yan (2006) show that brokers of insiders who are also market makers quote more aggressively on the day of the insider trade. Barbon, Di Maggio, Franzoni, and Landier (2019) show that brokers play a role in spreading order flow information in the stock market. Di Maggio, Franzoni, Kermani, and Sommavilla (2019) show that central brokers leak information generated by executing informed trades to their best clients. Again, these papers make a related – but fundamentally different – point: in this literature, the information advantage of the broker arises from knowledge of the order before its public revelation. Although interesting in its own right, such information advantage might be expected to dissipate when the insider trade is revealed publicly. In contrast, we show that the broker also has a different, more long-lasting information advantage, which exists even after the trade (the insider trade, in our case) is revealed publicly. This distinction is important for theory and policy on market fairness: information asymmetry arising from the trading process is long-lived, contrary to what is typically assumed in many theoretical and empirical studies.

Also, in the specific context of insider trading through brokers examined in some of these earlier papers, it is difficult to clearly rule out the possibility that the broker generated the recommendation and gave it to her clients, including the insider, who followed it, and therefore they all traded in the same direction. In other words, the broker's information advantage would have been there even if the insider did not trade through her at all, so the inside broker relationship is actually not important. In this paper, we address this possibility directly in a variety of ways and are able to rule it out, specifically examining the subset of first-in-a-regular-sequence trades. Our first-in-a-regular-sequence trade is an example of a trade that is not informed about anything at the firm, yet the inside broker acquires an information advantage through its execution – she knows that it is not information-driven. This kind of information advantage could not have arisen in the absence of a trade by the insider.

Finally, we also contribute to two broader literatures. We add to a large literature which documents that corporate insiders have an information advantage over outside investors (see, for example, Seyhun, 1986, 1998; Lakonishok and Lee, 2001; Bhattacharya and Daouk, 2002; Marin and Olivier, 2008; Cohen, Malloy, and Pomorski, 2012). We also contribute to the literature examining analysts'/fund managers' access to information through their interactions with firm managers (e.g., Coval and Moskowitz, 2001; Malloy, 2005; Bae, Stulz, and Tan, 2008; Cohen, Frazzini, and Malloy, 2008, 2010). Closest to our paper in this literature is the study of Green, Jame, Markov, and Subasi (2014), who find that access to management at broker-hosted investor conferences leads to more informative analyst research. The key difference here is that the information flow between firm insiders and analysts/fund managers is intermediated by brokers through the insider trading process, which highlights the role of brokers as an information intermediary.

The rest of the paper is organized as follows. Section 2 describes our data, Section 3 lays out our empirical framework, Section 4 presents our main results, Section 5 discusses some sources of the inside broker's information advantage, Section 6 presents results using alternaive samples, Section 7 examines heterogeneity in our evidence, and Section 8 concludes.

2 Background and Data

2.1 Background: Rule 144 and Form 144

Insider trading data and information about the broker used by the insider are obtained from Form 144 filings in the Thomson Financial Insider Filing database. This is a different source of information from Form 4, which is what most papers on corporate insider trading look at.

According to the Securities Act of 1933, stocks, bonds, and other securities must be registered with the SEC before being issued to the public. The registration process involves filing lengthy documentation and waiting for regulatory approval. However, companies are allowed to directly issue small numbers of shares without registration to someone as part of a compensation scheme, such as a stock bonus, pension, or profit-sharing plan, as well as in private placements. Under Rule 144, which was adopted in 1972, the people who obtained such unregistered shares of stock (restricted shares) are relieved of going through the registration procedures before being able to sell it publicly, subject to certain restrictions on the volume of sale and holding period. The text of Rule 144 explains that this rule is "designed to prohibit the creation of public markets in securities of issuers concerning which adequate current information is not available to the public. At the same time, where adequate current information concerning the issuer is available to the public, the rule permits the public sale in ordinary transactions of limited amounts of securities owned by persons controlling, controlled by or under common control with the issuer and by persons who have acquired the restricted securities of the issuer." Essentially, if the seller of a small number of unregistered securities isn't considered an underwriter, the seller is exempt from registering them. However, the seller is required to fill out a Form 144 before selling such shares, which must indicate the brokerage firm that will be executing the sale, the proposed date of the sale, and the proposed quantity. An example of Form 144, obtained from SEC's Edgar website, is presented as Figure IA.1 in the Internet Appendix (IA). For the vast majority of restricted stock sales the insider fills out a Form 144 and sells the shares on the same day. Thus, the execution day proposed in Form 144 is almost always the actual execution day. [1]

Table 1 in the IA lists the brokers we use. In Panel A, we list the distinct brokers used in the broker-affiliated analyst sample and Panel B lists the brokers used in the broker-affiliated mutual fund sample. Column (1) reports the name of brokers, column (2) the total number of Form 144 trades through each broker, and column (3) the dollar value of trades through each broker. Columns (4) and (5) show the value and number of Form 144 trades through each broker as a fraction of total dollar value and number of Form 144 trades through all brokers that have affiliated sell-side analysts (Panel A) or mutual funds (Panel B), respectively. Overall, our selected sample of brokers covers more than 80% of all Form 144 trades in terms of dollar value, and 75% in terms of number of trades. This suggests that the sample of brokers used in this study is representative. Finally, Table 2 in the IA shows that insider sales reported on Form 144 are – on average – indeed informative about future stock performance.

2.2 Data and Summary Statistics

We manually standardize broker names reported by different insiders in Form 144 and hand-match these names to I/B/E/S brokers. We use the mapping between broker identifiers and broker names from the 2007 vintage of I/B/E/S, since the latest vintage does not have this information. In our matching procedure, we carefully account for M&A activity and name changes by referencing publicly available sources. Information about investment banks involved in security issuances is obtained from the SDC Platinum database. Firm characteristics and stock returns/volume are obtained from the Compustat and CRSP database, respectively.

In Table 1 we present summary statistics for key variables used in our analysis. Our sample

[1] The Thomson Financial Insider Filing Data Feed Manual states that, "As a practical matter, most insiders file a Form 144 just prior to (or on the same day of) a sale." We verify this in a random sample of Form 144 filings, and find that the 'Approximate Date of Sale' to be the same as the 'Date of Notice' in 88% of cases, with the difference between them in all other cases being less than 3 days.

starts in 1997, which is the first year for which there is sufficient coverage of Form 144 data in the Thomson Financial Insider Filing database. Form 144 trades are summarised in Table 1, Panel A. After we match the Form 144 data to I/B/E/S, the resultant database covers 591,715 trades by insiders at 11,380 firms. The five most common brokers of insiders by the number of trades are Merrill Lynch, Citigroup, Morgan Stanley, Paine Webber, and Deutsche Bank Alex Brown. The median firm in our database has nine distinct insiders who traded during the sample period. Trades have a median size of $250,620, while the mean is close to $3 million. In years when there is at least one trade at a firm, there is an average of ten Form 144 trades. For the sample of firms that have more than one insider with a Form 144 trade, on average, four different brokers are used by different insiders of the firm. Within the sample of insiders who have more than one Form 144 trades at the same firm, 17.5% change their broker at least once. The average number of brokers used by these insiders at the same firm is 1.2.

In Panel B, we present summary statistics for the full sample of analysts, in Panel C for the sample of inside broker-affiliated analysts, and in Panel D on forecasts made by broker-affiliated analysts in periods where there is no connection (the pseudo-connect sample). We compare our estimated effects on analyst accuracy with respect to this pseudo-connect sample. In Panel E we present statistics on the Compustat and CRSP variables we use. Panel F of Table 1 provides information on the broker-affiliated funds sample. We get mutual fund quarterly holdings data from the Thomson Reuters mutual fund (S12) database. We define broker-affiliated mutual funds as those belonging to a fund family that is part of a financial conglomerate involving a brokerage house. We manually identify such affiliated mutual funds by parsing fund names in CRSP/ Thomson Reuters mutual fund databases containing names of brokerage houses. For example, "Wells Fargo Small Cap Fund" is affiliated with Wells Fargo's brokerage. We collapse multiple share classes of the same fund by taking the total net assets- (TNA-) weighted average of the individual classes' characteristics. The TNA of the fund itself is the sum of the TNAs of the individual classes that belong to the fund. Our data contains 215 distinct broker-affiliated funds involving 1,533 unique stocks. We identify 16 distinct brokers with affiliated mutual funds, and these brokers each have 13.4 affiliated funds on average. The mean TNA of broker-affiliated funds is 387 million USD.

Finally, we report summary statistics in Panel G on the profitability following these affiliated mutual funds' trades on connected stocks. Given that we do not observe the precise timing of the mutual fund trade within the quarter, we base our measures of profitability on returns in the quarter following the trade. Our main variable, Signed return, simply measures the returns to following the direction of a fund's stock trades. That is, it is the return on the stock if the fund increases its portfolio weight in that stock in the past quarter, and negative of the stock's return if the fund reduces the stock's weight.[2] We also construct another trading profitability measure which accounts for the size of the fund's trades, by multiplying quarterly stock returns (in percentage) by a categorical variable ranging from -5 to +5, depending on the magnitude by which mutual funds increase/reduce the weight of the insider's stock in their portfolios. Specifically, for all portfolio weight changes, we group them into 5 quintiles each on the positive and the negative side, with larger (absolute) numbers indicating larger changes in portfolio weight. Our summary statistics show that on average broker-affiliated funds have higher trading profitability than that of pseudo-connected funds (i.e., trading profitability of affiliated funds in periods when the firm insider did not trade).

3 Empirical Framework

In this section, we outline our empirical strategy. We start by identifying an appropriate ideal experiment, then explain the threats to identification caused by practical limitations, and lay out our tests addressing these limitations. To simplify exposition, we explain our empirical

[2] Fund's portfolio weight on a stock is defined as fund holdings in the stock (in dollar value, from form 13-F) scaled by the total portfolio value of the fund. All stocks that a fund held in some quarter but does not hold currently (conditional on the fund and stock existing) are counted as having zero portfolio weights in the current quarter.

strategy with respect to affiliated analysts' forecast accuracy. The same logic – and testing framework – also applies to affiliated mutual fund managers' trade profitability.

3.1 The ideal experiment

To identify the causal effect of executing an insider trade on a broker's advantage, one might think of an experiment that randomly assigns a broker to the insider each time he trades. We could then compare the accuracy of the analyst affiliated with this assigned broker against other analysts. However, this experiment does not capture any real-world advantage that a long-term broker chosen by the insider might have. For example, an insider might have a different level of communication with a broker who he chose – perhaps based on trust or ease of communication – and through whom he has been trading for years. The insider might talk to such a broker about issues that he might not with a randomly picked, one-trade broker.[3] So the ideal experiment needs to allow for a long-term relationship to form with a broker potentially chosen by the insider.

One such experiment would be to allow every insider to pick more than one – say, two – brokers with whom he could have a long-term relationship. Then, each time the insider wishes to trade, the experimenter would randomly pick one of these two brokers to execute that trade. One can then measure the information advantage of the broker selected for that trade, relative to the other broker. This would yield the causal effect of our interest.

In reality, however, we do not have such a setting. The main difference is the absence of the control broker with whom one can compare the information advantage of the actual broker facilitating the insider trade. Therefore, we need to compare the insider's broker with other

[3] E.g., an insider can casually mention to a long-time broker that he is selling stock to fund a major renovation of his house, or to buy a painting in an auction, etc.,; this information can be useful for the broker to infer that this transaction was not a bad-news motivated one. Moreover, a broker who knows the insider for a long time might be able to understand cues about the insider better than a one-trade one; e.g., notice that an insider, who typically hates travel, is calling from China to transact, implying that some Chinese acquisition talks are likely to have advanced.

brokers, some of whom may not provide a good counterfactual or benchmark. However, we can design a variety of different tests, exploiting the granular structure of the data, to take care of most of the important identification challenges that arise due to this issue. We start by using a difference-in-difference-in-differences (triple difference) design, implemented in a regression setting with three high-dimensional fixed effects (HDFE), as explained below.

3.2 Baseline HDFE approach

The HDFE approach (see, for example, Gormley and Matsa, 2014, 2016; Cvijanović, Dasgupta, and Zachariadis, 2016) allows us to address various endogeneity concerns more comprehensively than the traditional approach due to two main reasons. First, this approach accounts for unobserved heterogeneity in a more robust way, relative to the use of control variables. In the HDFE setting, most of the traditional controls are absorbed by at least one of the fixed effects – but these fixed effects account for other potential types of heterogeneity, even beyond what the literature has typically controlled for. Moreover, in this approach, one does not need to specify a parametric relationship between the dependent and explanatory variables (e.g., linear or in logs). Taken together, these advantages make HDFE analysis less susceptible to control variable or functional form mining/misspecification.

The panel regressions we run are of the form below:

$$Accuracy_{a,f,t} = \beta_1 + \beta_2 Connect_{a,f,t} + \beta_3 X_{a,f,t} + \delta_{f,t} + \gamma_{a,f} + \psi_{a,t} + \epsilon_{a,f,t} \tag{1}$$

where $Connect_{a,f,t}$ is the key variable of interest: it takes a value of one if an insider at firm f traded through a brokerage employing analyst a during period t (a quarter or a year, depending on the context, as described below), and zero otherwise. If the same analyst is employed at two different brokerage houses at different points, we allow the unobserved characteristics of the analyst to change across employment spells by treating them as if they were two different analysts. Additionally, we control for two other time-varying aspects of accuracy in $X_{a,f,t}$: an indicator for the parent of the brokerage house having an investment banking relationship with the insider's firm, and the vintage of the forecast, i.e., how far ago the forecast was released (to distinguish our effect from that of forecast recency). Finally, we include three groups of high-dimensional fixed effects, viz., (i) $Firm \times Time$ FEs ($\delta_{f,t}$), (ii) $Analyst \times Broker \times Firm$ FEs ($\gamma_{a,f}$), and (iii) $Analyst \times Broker \times Time$ FEs ($\psi_{a,t}$).

Given the granularity of our panel data structure, we can estimate all of these high-dimensional fixed effects simultaneously, making the fixed effects approach equivalent to a triple difference setting (Imbens and Wooldridge, 2007). To see this clearly, consider our definition of $Connect_{a,f,t}$ in Equation 1. An analyst A is "connected" to firm F in a particular period if an insider from that firm traded through the brokerage employing A right before.

i. $Firm \times Time$ FEs: To start, we can compare the accuracy of forecasts made by the connected analyst A against all other analysts covering firm F. This is achieved by using $Firm \times Time$ FEs. These FEs ensure that our estimated effect comes from comparing the inside analyst's forecast with forecasts of other analysts covering the same firm at the same time. These fixed effects, therefore, control for all time-varying firm characteristics, like firm size, book-to-market ratio, number of analysts, etc., as well as any firm-level event which might coincide with insider trades and affect accuracy. This set of FEs, then, account for any threat to identification at the firm-time level, e.g., that insiders could trade at a time when it is generally easier to forecast earnings (perhaps the timing of the insiders' trades systematically coincide with something else occurring at the firm which makes it easier to forecast earnings).

ii. $Analyst \times Broker \times Firm$ FEs: However, it is possible that analyst A may be better at forecasting firm F, in general, than other analysts. This could be related to the reason why the insider had picked this broker in the first place; for example, maybe the insider and the broker/analyst come from the same school. Alternatively, this could be because the brokerage house has another relationship with the firm throughout the sample period (e.g., a market maker or a book-runner) through which it can get an information advantage that trickles down to the analyst. To account for such general differences in analyst forecast accuracy, we include $Analyst \times Broker \times Firm$ FEs. Doing so allows us to contrast the quantity mentioned in the previous paragraph – the difference between the forecast accuracy of analyst A and the other analysts on firm F – in the time period following an insider trade, relative to other periods. [4] If any time-invariant links, like school ties or unobserved alternative relationships between the firm and the broker, were driving the difference in accuracy between analyst A and others, this difference would remain similar in periods with and without insider trades through A's brokerage, and, therefore, get absorbed by this set of FEs.

iii. $Analyst \times Broker \times Time$ FEs: Still, concerns might remain about whether the inside analyst (or the brokerage where she works) is somehow particularly accurate on all stocks – not just the insider's stock – at times after insider trades. We rule this out by using the fact that analysts typically cover multiple firms at the same time, allowing us to add $Analyst \times Broker \times Time$ FEs. All analyst-level time-varying variables, like the analyst's age, experience, number of firms covered, all-star status, etc. are absorbed by these FEs. Moreoever, estimating these fixed effects at the analyst-broker-time (rather than just analyst-time) level accounts for any time variation in broker-level variables, like broker size, resources, etc. that might change when the insider trades.

With the simultaneous use of these HDFEs, our estimated effect comes from comparing the

[4] In fact, we do a bit more by including $Analyst - Broker \times Firm$ fixed effects, which makes sure that we are comparing the forecast of the same analyst working at the same brokerage house at times with and without insider trades. (This is in contrast to using only an analyst-firm FE, which essentially includes comparisons of an analyst working for one brokerage (when the insider trades) with the same analyst at a different brokerage covering the same firm at a different time (without a trade)). This more granular fixed effect structure accounts for the possibility that the brokerage house assigns a better analyst to cover the firm in and around the periods when the insider trades through this broker. To make our discussion easier to follow, we drop the subscript b from Eq.1, where the unit of analysis, to be exact, is actually (a, b, f, t), and consequently the last two paired FEs are at the levels $\gamma_{a,b,f}$ and $\psi_{a,b,t}$.

improvement in the connected analyst's accuracy on the insider's stock following the insider trade, not only with any potential change in accuracy of other analysts covering that stock, but also with any potential change in her own accuracy on other stocks she covers at that time. Given this triple-difference nature of our specification, we need to separately control only for variables that vary at the analyst-/broker-firm-time level. We, therefore, incorporate as controls forecast age and investment bank affiliation, as explained before; our results hold even if we do not use these controls. Section 4.1.1 reports these results.

Our design for mutual funds follows the same structure, except that the main dependent variable in those tests is the profitability of a strategy that follows fund trades, Signed return, as described in 2.2. Also, we do not control for forecast age, which is not relevant in that context, but continue to control for investment banking relationships. These tests are described in more detail in Section 4.1.2.

In the following subsection, we look at the timing of forecasts relative to the insider trade, to further check for consistency of our interpretation.

3.3 Time variation in broker's information advantage

The data allows us to further design a test based on the inside broker's information advantage dissipating over time – based on the hypothesis that such an advantage is likely to be stronger when forecasts are revised closer to the insider trading date, if indeed they arise from such trades. This could happen if more information is revealed by the firm to the general public (e.g., through disclosure) over time, or if other non-affiliated analysts/fund managers become aware of the information driving the inside broker's advantage through alternative sources.

We examine analyst forecast accuracy at different horizons from the insider's trades. We expect the coefficient on the connect dummy to be insignificant before insider trades (similar to insignificant "pre-trends"), highest right after, and then decline with time if there are no further trades. Such evidence of sharp time-variation in the broker's information advantage surrounding the insider trade can lend support to our interpretation of results from Equation 1. Lastly, any lack of "pre-trends" will make reverse causality unlikely; we revisit this issue in the next section.

3.4 Ruling out time-varying unobserved links

The specification in Equation 1 makes it difficult for many alternative interpretations, but it does not rule out two particular concerns. First, the insider's firm and the analyst/ brokerage could share a different tie – e.g., market maker or book runner or pension plan trustee – which varies over our sample period, and which we are not measuring. While time-invariant ties are already accounted for by the $Analyst \times Broker \times Firm$ FE, if this tie yields the brokerage firm an information advantage particularly at times when there are insider trades, we might spuriously ascribe this advantage to the role of broker in facilitating the insider trade. For example, it could be that insider trades typically occur at times when there is valuable private information on the firm, and at these times, the brokerage firm also gets access to this information through its other relationship with the insider's firm. This could make the connected analyst's forecast more accurate exactly at times when the insider trades. Linking the higher accuracy of the connected analyst to information gleaned in processing the insider trade, however, would be spurious in this case.

Second, there is a possibility of reverse causality. Perhaps the analyst who works at the brokerage firm becomes better informed in certain periods and, via the broker of the insider, communicates that the insider should trade in this period. While this is perhaps less plausible than the concern above – since it is unlikely that a top executive who works for a company would look for private information on when to trade from an analyst working at a brokerage firm – we cannot rule it out completely using the tests above. This concern can be alleviated if we find no evidence of an inside broker advantage in the period preceding the trade (as mentioned in 3.3), but, again, it cannot be ruled out if the analyst's information advantage does not precede the insider trade but is exactly coincident with it.

We can, however, rule both of these concerns out using three distinct strategies. First, we use three falsification tests, based on analyst or insider job switches, and the insider changing brokers. Second, we exploit the fact that different insiders at the same firm use different brokers to trade in over 90% of our sample firms. Finally, we use a sub-sample of uninformative trades to rule out reverse causality and the broker having alternative access to important firm information. While this last test is based on a specific sub-sample of insider trades, it provides the cleanest setting for identification. We elaborate on these tests below.

3.4.1 Falsification tests

We can examine the plausibility of the concern mentioned above – brokers getting an information advantage through unobserved ties with the insider's firm at times when the insider trades – using the following two falsification tests.

i. Insiders changing their brokers: We examine insiders who changed their personal brokers. If the analyst employed at the insider's old brokerage is able to forecast better due to such unobserved ties, then this outperformance should continue even if the insider changes brokers. If, on the other hand, the insider's trading activity at the brokerage is the key driver, results should weaken/disappear when the insider-broker link is severed.

If we do not find any result in the placebo test, unobserved ties can only be a concern if the brokerage's other relationship to the firm also changes at the same time when the insider changes his broker. While this may sound unlikely, it is still possible: maybe when the firm changes its investment banking relationship, insiders discover that it is easier to move their personal trades to the new bank as well. Fortunately, however, we can use an alternative placebo test to address the same issue without relying on insiders changing brokers.

ii. Insiders changing jobs: Here, we focus on cases where the insider changes jobs, but retains her broker. We create another pseudo-connect dummy, equal to one when the analyst issues an earnings forecast on the previously connected firm following a trade by an unconnected insider at the same firm (who does not trade through this analyst's brokerage) within a year of the connected insider leaving the firm. If our results were coming from any unobserved time-varying connection between the insider's firm and the brokerage, and not the insider's trade, they are likely to remain similar if we examine the insider's brokerage firm's accuracy on his old employer -– the insider might have left the firm, but it is unlikely that the firm itself would change its market-maker or book-runner every time one of its many insiders leaves their job.

So, for our results to be driven by unobserved business ties, both of these placebo tests need to be invalid: that is, it needs to be true that the firm changes its business relationship with the broker's parent firm whenever an insider changes broker, and whenever an insider changes jobs. Taken together, this is perhaps implausible – especially since each firm in our sample has many insiders, making it unlikely that every time an insider changes her broker or her job, the firm will change its book-runner or market-maker.

Still, however, one other concern remains: it could be that the analyst has a better ability at forecasting the firm, but this ability is time-varying and is more likely to show up in the periods when the insider makes a trade. One example is that connected analysts have a superior ability to understand the insider's firm, and this ability is triggered particularly when the analyst's attention is drawn to insider trading activity. We rule this out by using a third falsification test, as described below.

iii. Analysts changing brokerage firms: Here, we look at analysts changing their jobs and moving to other brokerage firms. Suppose the affiliated analyst is better at forecasting the firm's earnings (especially in periods after the insider trades) for any of the other reasons mentioned above. Then, this (time-varying) ability should continue if she moves and starts to work for a different brokerage house while still covering the same firm. On the other hand, if this higher accuracy was indeed coming from information gleaned in the process of the insider trade intermediated by her former employer, it should dissipate when she changes jobs.

Results from these falsification tests are presented in Section 4.3.

3.4.2 Exploiting the presence of multiple inside brokers in each firm

There are multiple insiders at most firms. Each of them can use their own personal broker to trade, resulting in 90.3% of firms in our sample having multiple inside brokers. Here we exploit this particular feature of the data to rule out concerns surrounding unobserved ties between the insider's broker and his firm, particularly those that might arise from the insider choosing his broker.[5]

First, even if the above alternative channel is an important conduit of information, it is less likely to affect all the brokers used by all firm insiders. Instead, it is likely to be a more important concern for brokers shared by many insiders at the firm, especially since it is possible that the firm is somehow instrumental in recommending that broker to its insiders in the first place.

In order to test if our results are indeed driven by those brokers that are used by a majority of firm insiders, we conduct a test where we run the regression in equation 1 only using non-major brokers — defined as less popular brokers, used by less than a quarter (robust to half) of a given firm's insiders. These brokers are less likely to have an unobserved affiliation, as compared to the most popular broker at the same firm. If we can show that our main results go through with these non-major brokers, unobserved affiliation is less likely to be a concern.

To further examine this evidence, we conduct an additional test using this sample of non-major brokers. The idea is to examine cases where an insider at the firm trades through a non-major broker, but there is no other insider who trades through the firm's major broker at the same time. If an inside broker's information advantage is indeed driven by intermediating insider trades, then the non-major broker would get an information advantage at this time –

[5]We thank an anonymous referee for pointing us in this direction.

but, crucially, the major broker should not have any such advantage. On the other hand, if the major broker has an unobserved relationship with the firm – and this relationship gives him an advantage particularly at times when firm insiders trade – the major broker should still have an advantage over others, even when some other insider trades through the non-major broker.

Moreover, in the alternative explanation, a broker who has a different link to the firm is more informed around insider trades because some information/event happens at the firm; the broker's information advantage is higher around this event, and the event coincidentally drives insider trades. Suppose this is true – insiders do trade when there is some type of information or event at the firm. However, it is highly unlikely that all insiders always trade whenever the event happens. If – at least in some cases – a subset of insiders trade around the event, while others do not, then only the brokers of the first group of insiders are likely to get an information advantage if the trade itself is the conduit of information. On the other hand, under the alternative unobserved-firm-broker-ties story, there is no reason for the particular set of brokers whose client insiders traded to be differentially informed. So, this variation in who trades allows us to rule out that the information related to the event itself – and not the trade – is driving the broker's advantage.

In order to test this, we restrict our sample to brokers who are connected to firm insiders. In presence of $Firm \times Time$ fixed effects, the coefficient on the connect dummy here identifies the incremental information advantage of brokers who have a client trading during this period, relative to other brokers who also have a client at the same firm – but their clients did not trade at this time.

This test also helps rule out other concerns that can arise from endogenous broker choice resulting in connected inside brokers being systematically different from others. This is because even if broker choice is endogenous, there is a rotation between treatment and control brokers in this setting. That is, when insider I_1 trades through his broker B_1 and insider I_2 at the same firm does not, B_1 is the treated broker, and B_2 (insider I_2's broker) is the control. At other times when I_2 trades but I_1 does not, treatment and control roles reverse – i.e., B_2 is then the treated broker, and B_1 is the control. Systematic differences between treated and control brokers – even if treatment is non-random – are, therefore, unlikely to affect these results.

These test results are in Section 4.4.

3.4.3 Using a sample of uninformed trades

In another distinct test, we use a sub-sample of insider trades – those that are part of a regular trading sequence, e.g., in the same month every year – to rule out the identification concerns mentioned in the beginning of section 3.4 in a relatively clean setting.

Cohen, Malloy and Pomorski (2012) show that such regular trades are not informative about future returns on average, which we verify using Form 144 trades. This is also true for the very first trade in the regular sequence, but the market will not know this until participants realize that this is going to be repeated in the future. The analyst affiliated with the insider's personal broker might, however, know about the non-informativeness of the trade; for example, from trading instructions. This gives the connected analyst an advantage relative to other analysts who build in a positive probability of the trade being informed into their forecasts.

So, we can design a test where we check if the inside analyst's relative information advantage is the strongest for first-in-sequence insider trades. Since such uninformed sequence trades are not ideas that could have plausibly arisen from the analyst, this setting can provide evidence that the direction of flow of information is from the insider to the analyst and not the other way round. Hence, this rules out reverse causality.

At the same time, this test can also rule out the alternative explanation of unobserved ties between the brokerage and the firm driving our results, since that explanation is based on the brokerage firm becoming informed about some firm-level information or event through its tie and not through the insider trade. Here, there is no special information or event at the firm driving the trade – so nothing that the broker can be informed about through any other ties.

Yet, there is an information advantage; that advantage comes purely from the knowledge that the trade itself is not information-driven.

Results from these tests are described in more detail in Section 5.1.

3.4.4 Cross-sectional analyses

Finally, we examine where in the cross-section of analysts and firms are our results stronger. These tests help us understand the mechanism through which information transfer takes place. For example, the affiliated analysts' information advantage is likely to come from their interaction with trading desk colleagues who execute insider trades. To check whether this is true in the data, we conduct a job-tenure-based test and a geography-based test. In these tests, we check if analysts who have worked in their firms longer, or are based out of the same location as the insider's broker – and are, therefore, more likely to have closer interactions – have a greater advantage. Similarly, we can check if our effects are stronger for smaller, higher R&D intensity, higher growth firms, on which there might be more room to benefit from any additional information. These tests are explained in more detail in Section 7.

Overall, while we may not have an ideal experiment in our setting to assess the causal effect of facilitating insider trades on affiliated analyst's/fund manager's information advantage, we can design a variety of tests to address various concerns arising out of non-random assignment. Taken together, these tests make it implausible that our results are spurious.

4 Empirical Results

4.1 Baseline Results

In this section, we report results from the specification discussed in Section 3.2.

4.1.1 Forecast Accuracy of the Inside Broker-affiliated Analysts

To begin, we measure forecast accuracy using analysts' annual percentage absolute EPS forecast error (PAFE). We focus on annual earnings forecasts in I/B/E/S, following the literature (e.g., Clement, 1999; Malloy, 2005; Hong and Kacperczyk, 2010; Bradley, Gokkaya, and Liu, 2017), as these are the most commonly issued types of forecasts. However, our results also obtain using quarterly earnings forecasts (as we show in Table 6 in the IA). The PAFE for analyst i on stock j in fiscal year t is equal to the absolute value of an analyst's latest forecast, minus actual company earnings (drawn from the I/B/E/S Actuals File), as a percentage of the stock's price 12 months prior to the earnings announcement date.

$$PAFE_{i,j,t} = \frac{100 * |Actual\ EPS_{i,j,t} - Forecasted\ EPS_{i,j,t}|}{Price_{j,t-1}} \tag{2}$$

Then we run panel regressions of PAFE, introducing different types of fixed effects, culminating in the specification in Equation 1 from Section 3.2.

Columns (1)-(4) of Table 2 reports these regression results. In column (1), we add firm, year, and brokerage fixed effects. The negative coefficient on the connect dummy indicates that analysts are more accurate after a firm insider trades through the brokerage employing her. In columns (2), we add paired fixed effects at the firm-year and analyst-broker-firm levels. The coefficient on the connect dummy is still significantly negative, although the magnitude is reduced by half. In column (3), we add a comprehensive set of HDFE, including firm-year, analyst-broker-firm, and analyst-broker-year fixed effects, as explained in Section 3.2. In column (4), we also control for covariates that vary at the analyst-firm-time level, and are, therefore, not subsumed by these HDFEs. In particular, we control for forecast age (log number of days from forecast announcement day to the earnings announcement day) and any underwriting affiliation between the brokerage's parent company and the firm (Clement, 1999; Lin and McNichols, 1998; Hong and Kubik, 2003).

The economic magnitude of the increase in relative forecast accuracy for the connected analysts can be understood as follows. The mean of PAFE across our sample of analysts who are connected to a firm at some period, but not connected currently, is 0.72 (Table 1, Panel D). Hence our coefficient in column (4), for example, represents a 10.5% reduction (coefficient of 0.0756, relative to a sample mean of 0.72) in average forecast errors (t=-2.78). This is an economically significant reduction, especially given that (i) the magnitude is measured with respect to the analyst's own forecast accuracy in periods without the inside information advantage, and (ii) the effect we capture is an average "intention-to-treat" effect – the link we identify captures the potential for information transmission, but does not allow us to exclude cases where there was no information transmitted in the trading process.

Next, in column (5) of Table 2, we replace our PAFE measure by Target Price Error, defined as follows.

$$\frac{100 * |Price_{j,t+12} - Target\ Price_{i,j,t}|}{Price_{j,t-1}} \tag{3}$$

Our result shows that the connected analysts' information advantage also extends to forecasting slightly more accurate target prices, but the effect is economically less pronounced than it is for short-horizon earnings forecasts. The result shows that the connected analysts are 3.5% more accurate in their target price forecast (coefficient of 0.0203, relative to a sample mean of 0.584). One possible reason for this is that insiders are likely to have better information about future earnings than future prices; hence, if brokers facilitate the flow of this information to analysts, we might expect them to be better at forecasting earnings than prices.[6]

Finally, in the last column of Table 2, we examine a dummy variable, *Most accurate*, which takes a value of one for an analyst at time t if her forecast is the most accurate among all analysts covering that firm during the year. Again, our results show that the connected analyst is 16.6% more likely to be the most accurate (a coefficient of 0.0243, compared to an unconditional

[6] We thank our referee for pointing this out to us.

likelihood of being the most accurate of 14.6%).[7]

We conduct a variety of other tests to understand the robustness of our results, which we report in the IA. First, in Table 3 in the IA, we find that winsorizing PAFE at different thresholds, using stock prices one month or one quarter prior to the earnings announcement date to scale absolute forecast errors, or controlling for forecast frequency and firm-specific relative experience (which have been shown by the literature to affect analyst forecast accuracy) does not affect our results. Second, we show in Table 4 in the IA that even if we use a fixed sample so that we have the same number of observations across the columns (to make the different FE specifications in Table 2 more comparable), similar conclusions obtain. Third, we examine the alternative explanation that connected analysts are less optimistic on average, and therefore more accurate given the overall optimism bias of analysts previously documented, and find no such evidence (Table 5 in the IA indicates that connected analysts are neither systematically optimistic nor pessimistic). Next, in Table 6 in the IA, we show that using analyst forecasts on quarterly earnings (and redefining Connect as a dummy equal to one if the analyst issues an earnings forecast on a stock within one quarter after the firm's insiders trade through her affiliated brokerage) does not have any material impact on our conclusions. Lastly, although our main tests incorporate the HDFE set-up, our results are also robust to the more traditional approach taken in the literature of using a variety of control variables.

[7] In unreported results, we also examine getting selected as an "All Star" analyst. The dependent variable is an "All star" dummy variable that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in the annual polls in the Institutional Investor magazine. We use the same HDFE framework except that we cannot control for analyst-broker-time fixed effects, since the dependent variable is an analyst-time characteristic (this is why we chose not to report these results in Table 2). The result shows that being connected through an inside broker relation significantly increases the probability of being elected as an "All Star" analyst by 11.8%, relative to the unconditional probability of being an All-Star analyst in any year (the coefficient on the connect variable in this test is 0.01, relative to the unconditional probability of 0.0845).

4.1.2 Trade Profitability of Inside Broker-affiliated Mutual Funds

In this section, we examine whether the inside broker advantage is also used by affiliated mutual funds to trade more profitably on the insider's firm. Broker-affiliated mutual funds are defined as mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house.

We first focus on broker-affiliated funds' trading following Form 144 trades. If affiliated funds benefit from the inside broker's information advantage, we expect these funds' own trades, in turn, to generate higher returns. Specifically, following insider trades through a brokerage, if affiliated funds increase (decrease) the weight of the insider's stock in their own portfolios within 90 days, we should see positive (negative) subsequent returns on that stock. We refrain from analyzing the performance of the entire fund because trading a few connected stocks profitably need not have a statistically discernable impact on overall fund performance.

We start by analyzing signed stock returns (as described in Section 3), in the following setting:

$$Signed\ Return_{i,m,t+1} = \beta_1 + \beta_2 Connect_{i,m,t} + \beta_3 X_{i,m,t} + \delta_{i,t} + \gamma_{i,m} + \psi_{m,t} + \epsilon_{i,m,t} \qquad (4)$$

where $Signed\ Return_{i,m,t+1}$ equals the return on stock i in quarter $t+1$ if mutual fund m increased that stock's weight its portfolio in quarter t, and the negative of the return on stock i if fund m reduced its position. $Connect_{i,m,t}$ is a dummy equals one if an insider at firm i traded through a brokerage affiliated with fund m in quarter t. We use a $Stock \times Time$ FE (analogous to $Firm \times Time$ FEs in Equation 1), in addition to $MutualFund \times Stock$, and $MutualFund \times Time$ FEs.[8] For $X_{i,m,t}$, we use the investment bank affiliation variable as

[8] We cannot use $MutualFund \times Broker \times Stock$, and $MutualFund \times Broker \times Time$ FEs, since, unlike analysts, in the sample of funds many are not affiliated with any brokerages.

described in Equation 1.

Table 3, Columns (1)–(4) present these results in the same format as Table 2. The results uncover evidence of significantly higher future profitability from following the direction in which inside broker-affiliated funds trade. For example, the result in column (4) indicates that the average stock in which an affiliated fund increases (reduces) its portfolio weight earns 89 basis points (bps) more (less) in the quarter following an insider trade through her brokerage compared to its trading profitability on the same stock in other quarters. Again, the inclusion of HDFEs means that this 89 bps is the incremental returns from following an affiliated fund after the insider trade, not only relative to any potential change in profitability of following non-affiliated funds holding that stock, but also with any potential change in following the same fund on other stocks it holds at that time.

In column (5), we take into account not only the affiliated fund's trading direction, but also the magnitude by which it increases/reduces the weight of the insider's stock in its portfolio. The dependent variable here is next-quarter stock returns (in percentage) multiplied by a categorical variable ranging from -5 to +5, depending on the degree to which the affiliated fund changed that stock's weight in its overall portfolio. That is, we divide all stocks in which the fund increased its position into five quintiles (from 1 to 5, with larger numbers indicating bigger changes in portfolio weight following the insider trade); similar logic applies for stocks in which the fund reduced its position. In terms of portfolio strategy, this is equivalent to adjusting the leverage of the portfolio in consonance with the strength of the fund's trading signal: the stocks in the fifth quintile (bought/sold most heavily by funds) have five times the leverage of stocks in the first quintile (that have more or less similar weights in the fund portfolio as in the previous quarter). To interpret the economic magnitude of the coefficient, note that the average leverage of the long/short side of the strategy here is 3:1 (e.g., the leverage for each of the quintiles of stocks bought by funds are 5:1, 4:1, 3:1, 2:1 and 1:1, similarly for stocks sold). So if the trading signal strength did not matter beyond just the direction of the affiliated fund's trade, one would expect the incremental profitability of this strategy to be 267 bps per quarter (three times that of the coefficient in column (4)). The actual coefficient is 412 basis points, which suggests that signal strength, i.e., the degree to which affiliated funds adjust their portfolio weights following insider trades, is additionally informative. For simplicity, we present results from the unlevered strategy of column (4) in the rest of the paper.

We examine the robustness of these affiliated fund results in Tables 7 and 8 in the IA. In Table 7 in the IA, we examine a calender-time portfolio strategy which exploits the inside broker-affiliated funds' information advantage. The strategy goes long (short) in the stocks associated with Form 144 trades more heavily bought (sold) by broker-affiliated funds' than non-affiliated funds', and produces significant alphas. No such profits obtain on the same set of funds' trades on other, non-connected stocks at the same time, or their trades on the same connected stocks at times when the insider does not trade through their brokerage. In Table 8 in the IA, we examine the profitability of following affiliated funds in a panel regression approach with stock returns as the dependent variable and HDFEs for fund-broker-stock and fund-broker-time. Since stock returns vary by stock-time, we cannot include a stock-time FE, like in our baseline fund specification in Equation 4. Instead, we incorporate a $DGTW-portfolio \times Time$ FE and continue to find similar profitability from following affiliated fund trades.

In sum, our evidence indicates that following the trading pattern of inside broker-affiliated funds leads to a profitable trading strategy over the quarter following fund trades, and these results are robust to significantly different empirical strategies.

4.2 Examining Timing

Next, we examine the hypothesis (from Section 3.3) that the inside broker's information advantage is likely to be stronger the closer forecasts/trades are to the insider trading date. To test this hypothesis, we examine analyst forecast accuracy/fund trading profitability at different horizons from the insider's trades. We define three levels of closeness in time to insider trades: forecasts or fund trades made within 90 days following insider trading date, forecasts or fund trades between 90 and 180 days following insider trades, and forecasts or fund trades made more than 180 days following insider trades. In addition, we also construct a dummy indicating those forecasts or fund trades made up to 90 days before the insider trading date. This last dummy serves like a "pre-trend". If the information indeed flows from inside brokers to affiliated analysts/fund managers, we should expect the coefficient on this particular dummy to be insignificant.

Table 4, Panel A reports the results of a panel regression of PAFE on the interaction between the *connect* dummy and the four dummies indicating the timing of the forecast relative to the insider trading date. Panel B shows a similar result examining the return predictability of broker-affiliated fund trades. Consistent with our hypothesis, the inside broker advantage is strongest when the forecasts and trades are the closest to the insider trading day. The benefit derived from the inside broker affiliation becomes weaker when the affiliated analyst's forecast/ fund's trade is further away in time relative to the insider trading date, becoming insignificant when forecasts/trades are made more than 180 days after. Moreover, the coefficients on the dummy for both analyst forecast and fund trades made up to 90 days before insider trades are also insignificant, as expected.

Finally, in the Internet Appendix, we examine whether affiliated analysts issue new forecasts shortly after becoming more informed through the broker processing an insider trade. Although the earlier tables control for forecast vintage, if there was information flow, an analyst might want to update his or her forecast.[9] To test this hypothesis, we run a firm-broker-quarter panel regression. The dependent variable is a dummy indicating whether the broker had an updated

[9]Note, however, that it is not essential in our framework for the affiliated analyst to update her forecast after an insider trade. As an example, consider an insider trade that constitutes the beginning of a routine sequence (as in Section 3.4.3). After the insider trades, analysts not affiliated with the inside broker – who have no way yet to know that this trade will belong to a future sequence – might think this is an information-driven opportunistic trade. They might, therefore, revise their forecasts, while the affiliated analyst might retain hers.

forecast for that firm in that quarter. The independent variables are various time dummies measuring the time in quarters relative to insider trades from that firm. Specifically, *t-1* is a dummy variable that equals one in the quarter before the insider trade. We split the quarter in which the insider trades into the pre and post periods relative to the timing of the trade. *t0-pre* (*t0-post*) is a dummy that equals one for the period before (after) the insider trade within the quarter in which the insider trades. Similarly, *t1* and *t2* are time dummies that turn on one and two quarters, respectively, after the insider trade. *Connect* is a dummy that equals one for the analyst affiliated with the inside broker. Each of the time dummies is further interacted with the *connect* dummy to understand the differential propensity for the affiliated analyst to update her forecast following an insider trade through her brokerage. The results in Table 9 in the IA show that connected analysts are indeed more likely to issue a forecast than non-connected analysts in the same quarter of insider trades. However, they are no more likely than non-connected analysts to update forecasts in the quarter preceding or following that quarter. Even within the quarter of the insider trade, the affiliated analyst is significantly more likely to update her forecast after the insider trade, but not before it.

Overall, these results show that the precise timing of the insider trade does play an important role in determining when the inside broker has an information advantage.

4.3 Falsification Tests

In this section, we present results from falsification tests, as explained in Section 3.4.1. These results are reported in Table 5; Panel A presents results for affiliated analysts and Panel B for fund managers.

i. Insiders changing their brokers: We examine insiders who switch to a different broker to execute their trades, but continue working for the same firm. In columns 1 and 2 of Panel A, we create a pseudo-connect dummy equal to 1 when the analyst at the no-longer-connected brokerage issues an earnings forecast within a year following the insider's trade through the new broker. The coefficient on the pseudo-connect dummy is close to zero and not significant, while the connect dummy continues to retain its significance. Similarly, in the first two columns of Panel B, we look at a strategy following fund managers affiliated with the insider's old brokerage. Again, following their trades lead to no incremental returns. The economic magnitude of the pseudo-connect coefficient is also much smaller than that of true connect dummy, so the insignificance is not simply due to smaller sample size.

iii. Insiders changing jobs: In columns 3 and 4 of both panels, we focus on cases where insiders change jobs but retain their broker. In Panel A, we create another pseudo-connect dummy, equal to one when the analyst issues an earnings forecast on the previously connected firm, following a trade by an unconnected insider at the same firm (who does not trade through this analyst's brokerage) within one year of the connected insider leaving the firm. Similarly, in Panel B, we examine the returns to following an affiliated fund's trades in the insider's old firm, but after the insider leaves his job and so the inside broker link is severed. That is, we follow the same fund's trades after a different insider in the same firm – who does not use the brokerage affiliated with the fund – trades. Just as in the previous columns, the coefficient on the pseudo-connect dummy is insignificant.

iii. Analysts changing brokerage firms: Finally, consider an analyst who continues to cover the same firm as he did for the inside broker, but now moves to a not-connected brokerage house (a brokerage house that does not facilitate trading for any insider at that firm). We define a pseudo-connect dummy equal to one when such an analyst issues a new forecast after the firm insider trades through the old broker (that the analyst no longer works for). We then regress PAFE on this pseudo-connect dummy, with and without the true connect dummy. The results are reported in columns 5 and 6 of Panel A. Panel B reports the analogous result for fund managers changing their jobs to a different fund family, which does not have any brokerage relationship with the firms' insiders. Again, there is no evidence of an inside broker advantage once the link is broken. This suggests that being co-workers in the same organization facilitates the type of information-sharing we focus on since a personal relationship between an analyst/manager's and the broker is unlikely to cease as soon as they changed jobs.

As mentioned before, these tests help rule out the hypothesis that our connect dummy is proxying for some omitted time-varying connection between the brokerage and the insiders' firm, such as the firm having multiple book-runners (we already control for lead underwriting in our tests), or any other such unobserved affiliation. Had our results been reflecting any such unobserved time-varying connection between the insider's firm and the brokerage, they would most likely have remained similar when we examine the accuracy of the insider's previous brokerage on his firm, or the inside broker's accuracy on the insider's old firm when he changes jobs. These results also help rule out another alternative hypothesis: time-varying information flows between insiders and analysts/funds, arising, for example, out of social ties. If our results were indeed driven by such ties, we should find the pseudo-connect coefficient to be just as significant, since switching to a not-connected broker should not affect the social tie between the analyst or fund manager and the firm insider.

In summary, our falsification tests all reinforce the notion that the channel through which the broker-affiliated analysts and fund managers obtain their information advantage is the insiders' brokerage relationship.

4.4 Multiple inside brokers at each firm

In this section, we present results from further tests to address the concern that our results are driven by some unobserved relationship between the insiders' firm and brokerage, e.g., something related to the drivers of the insider-broker match itself. As mentioned in Section 3.4.2, about 90% of firms have different insiders trading through different brokers. Within these firms, we can identify brokers that are used only by a few insiders ("non-major brokers"). If firm insiders are indeed likely to use the firm's underwriter/book-runner etc. as their personal brokers (and our results are picking up an information advantage that results from these unobserved relationships), then we could, in principle, try to identify that broker. Here we hypothesize that such a broker is likely to be the "major broker" at the firm – a popular broker used by a large number of firm insiders. Then, if we still find significant results when focusing on the subset of insider trades through other, "non-major brokers", the concern that our result is driven by unobserved firm-brokerage relationship could be minimized.

To operationalize the idea, we first define "major broker" as a broker used by more than 25% (or 50%) of insiders in a firm. We then construct a connect dummy based on insider trades through only the "non-major broker", and redo our empirical tests. The results are reported in Table 6. Panel A reports results on analysts, and Panel B on funds. In both settings, the evidence is economically and statistically similar to what we find using the full sample, regardless of how we define major and non-major brokers. This suggests that the "inside broker" channel we propose is unlikely driven by any unobserved firm-brokerage relationship.

In Table 7, we present further evidence from a test examining whether major brokers continue to have an advantage when an insider trades through a non-major broker at the same firm. Specifically, in Panel A, we regress analyst forecast errors (PAFE) on a Connect dummy, which is equal to 1 when the analyst employed by the major broker of a firm issues an earnings forecast after the firm's insider trades through a non-major broker of the same firm. Panel B reports similar results on the profitability of broker-affiliated fund trades. We find that major-broker-affiliated analysts/funds do not get any information advantage when insiders trade through non-major brokers, again consistent with the information advantage of the inside broker indeed having something to do with intermediating insider trades, rather than to an unobserved affiliation.

Next, in Table 8 we conduct another test exploiting multiple inside brokers at the same firm, where we restrict our sample to only those brokers who have at some time facilitated an insider trade at that firm. In the presence of $Firm \times Time$ fixed effects, the coefficient on the *connect* dummy identifies the incremental information advantage of brokers who have a client trading during a particular period, relative to other brokers who also have a client at the same firm – but whose clients did not trade in that period. These results are very similar to our baseline results in Tables 2 and 3.

As mentioned in Section 3.4.2, the benefit of this last test is that every treated broker in the current period (who facilitates an insider trade in that period) is the control broker in a different period (those who also facilitated insider trades at the same firm, but not in this period). Hence, these results are less subject to concerns regarding any alternative hypothesis based on endogenous firm-broker matching.

5 The Inside Broker's Information Advantage: Channels

We gave a couple of examples in the introduction on the nature of the trading instruction being one potential source of the inside broker's information advantage. Clearly, many other channels could also convey similarly valuable information: for example, the broker might know whether the insider sale was accompanied by sales of other unrelated stocks that the insider owns (more likely to be liquidity trade). Or, if the insider uses the same broker for trades in his close family members' (e.g., children's) accounts, the broker might know whether all of these accounts have been selling the firm's stock recently. The market is unlikely to have this type of information, which the broker might possess purely incidentally. At the same time, such information could be helpful in inferring whether a particular trade was more likely information or liquidity driven.

In addition, the broker might become aware of other kinds of information in the process of his interaction with the insider, such as whether the sale was motivated by a desire to purchase some asset, like a house or a yacht. It is also possible that the broker can infer from vocal cues or body language the insider's views on some aspects of the company's business (Mayew and Venkatachalam, 2012). In sum, there are various clear reasons why one might expect the insider's broker to be privy to information that would help him understand the motives behind the trade better than other market participants.

Although it is difficult to find direct evidence on many of these channels, there is testimonial evidence in favor of at least one of the channels we mentioned above – that of the broker figuring out information from trades made by the insider's family members at the same time as the insider. One example is the case involving ImClone Systems. The ImClone insider trading scandal resulted in a widely publicized criminal case, and prison terms, for media celebrity Martha Stewart, ImClone chief executive officer Samuel D. Waksal, and Stewart's broker at Merrill Lynch, Peter Bacanovic, who inferred bad news from trades made simultaneously by Waksal and his other family members (this channel was discovered by the prosecution later, during their investigation).

5.1 Uninformed Trades: Start of a Repeated Trading Pattern

In general, it is difficult to show definitive evidence of what the broker might know that gives an edge to a broker-affiliated analyst/fund manager even after the related insider trade has been publicly disclosed. This is because the source of such information is likely to be unobservable to the econometrician. All we can do as econometricians is to look for evidence of the following nature: something that eventually becomes clear to everyone including non-affiliated analysts/fund managers, that only the affiliated analysts/fund managers could have known earlier – i.e., at the time of the trade itself – giving him a clear advantage at that time.

One example is the start of a routine (i.e., repeated) trading pattern, as mentioned in Section 3.4.3. We identify routine trades following Cohen, Malloy and Pomorski (2012), as insider trades that occur in the same calendar month for three consecutive years. Within all routine trades, we then define three dummy variables for those that occur for the first time in the sequence, for the second time in the sequence, and the third time or after. This routine trading pattern would become clear to all participants only after a few consecutive years. However, it is possible that the broker knew that this was the insider's plan right when he implemented the first or second trade according to the pattern. To test this hypothesis, we start by contrasting the forecasts of inside broker-affiliated analysts with that of non-affiliated analysts around such trades.

First, consider a first-in-sequence routine insider trade. After the insider sells, we should observe that analyst not affiliated with the inside broker – who have no way yet to know that this trade will belong to a future sequence, and, therefore, think this could be an information-driven opportunistic trade – negatively update their forecasts on the insider's stock. If the affiliated analyst knows that this is the start of a sequence, he should be much less negative on the stock. Now consider the same insider's trades that come later in the same sequence, i.e., trades in the same month in subsequent years. By this time, even the non-affiliated analysts would be able to spot the pattern and infer that these are likely to be uninformative sequence trades. Therefore, their forecasts should be similar for the trades later in the sequence.

These results are reported in the first column of Table 9, Panel A. The dependent variable is the analyst forecast optimism (signed forecast error). Consistent with our prior, we find that the inside broker-affiliated analysts remain relatively more optimistic than their peers about the future prospects of the insider's firm after observing the first-in-sequence trades. This relative optimism decreases monotonically from the first-in-sequence trade to the third-or-further-in-sequence trade.

In column 2 we examine analyst forecast accuracy using our baseline PAFE measure. Here the coefficient on the connect dummy monotonically decreases from the first-in-a-sequence trade to the third-or-further-in-a-sequence trade. While the connect coefficient is -0.10 following the first-year routine trades, it is smaller and becomes insignificant following the second-year routine trades. The economic magnitude of the connect dummy on the first-year routine trade is even larger than that of the non-routine trades, though statistically, it is less significant due to the smaller sample size.[10]

In Panel B of Table 9, we repeat this analysis for inside broker-affiliated mutual funds. We again use our previously defined dummies differentiating between routine trades that occur for the first, second, or three or more years into the sequence. In column 1, the dependent variable we use is an indicator, which takes a value of 1 (-1) if the fund increases (reduces) the weight of a stock in its portfolio. Similar to the results for analysts, we find that the difference in optimism on connected stocks between affiliated and non-affiliated funds decreases monotonically from the first-in-sequence trade to the third-or-further-in-a-sequence trade. While affiliated funds' holding of the insider's stock is likely to increase with a 10% higher probability (t=5.52) compared to other funds following the first-year routine trades, the difference becomes smaller and insignificant following the second-year routine trades. The difference further decreases to close to zero following the third-year (or beyond) routine trades. Finally, broker-affiliated funds trade more negatively than peers when the trade is indeed opportunistic (i.e., not routine), suggesting that they are better able to sort out opportunistic trades from potentially repeated and uninformative ones.

In the second column of the same panel, we verify that the direction in which the broker-affiliated funds change their portfolio weights following the first-in-sequence insider trade is indeed profitable. In the HDFE setting with our usual signed stock return variable (recall that the sign reflects whether a fund increases or reduces its holdings of that stock), we find that following affiliated funds' trading direction leads to 46 bps per quarter higher returns, compared to non-affiliated funds, following a first-in-sequence insider trade through their brokerage. On the other hand, non-routine Form 144 trades do predict negative future returns on average, so broker-affiliated funds avoid significant losses by selling these stocks more aggressively than their peers (the coefficient on the "Connect non-routine" dummy in the second column suggests

[10]There are 915 observations on connected first-in-a-sequence trades, 961 observations on connected second-in-a-sequence trades, 938 observations on connected further-in-a-sequence trades, and 15,379 observations on connected non-routine trades.

an 89 bps higher return to following affiliated funds' trade).

Overall, both the analyst and broker-affiliated mutual fund results support our conjecture that inside brokers indeed get information beyond that contained in the public disclosure of the insider trade itself.

The results in this section help rule out reverse causality, as explained briefly in Section 3.4.3. Our example of the first-in-sequence trade here is one that is not particularly informed about anything at the firm. Still, for the affiliated analyst/fund manager to have the kind of edge we find, the inside broker's information advantage must reflect his knowledge of something that others do not know. Therefore, the inside broker's advantage has to be related to trading by the insider. If the insider did not trade at all, these affiliated fund managers/analysts could not have obtained their advantage, which comes from the proverbial 'red herring' nature of these trades.

6 Alternative Samples

In this section, we examine our evidence using three alternative samples.

6.1 Are our Analyst and Fund Results Really Distinct?

The consistent results we obtain using two distinct settings suggest the information advantage broker obtains through processing insider trades is pervasive, and unlikely to be spurious. However, one may doubt whether the analyst and mutual fund settings we use are truly two independent settings. For example, it could be the case that a brokerage firm has both affiliated analysts and mutual funds, and the information advantage the connected analyst possesses on the insider's firm (through the inside broker relation) also passes to the affiliated fund managers. In this case, our results should not be claimed as distinct.

In this section, we rule this out by removing any overlaps between affiliated analysts and affiliated fund samples. In particular, we keep only the analysts at brokerages that do not have affiliated mutual funds. Similarly, for the mutual find sample, we remove those broker-stock combinations where an analyst from the affiliated brokerage covers that stock. We then redo our tests using these two independent samples. The results are reported in column (1) of Table 10. Panel A reports results from a panel regression of analyst percentage absolute forecast error (PAFE) on the connect dummy. Panel B reports results on signed returns (in percentage) to following affiliated fund trades. Our results still hold in both these subsamples.

6.2 Removing Trades of Insiders Who Can Influence their Firm's Business Relationships

A second alternative sample we examine is to use only those Form 144 trades from non-top insiders, defined as those corporate insiders who are not CEO, CFO, the President or the Chairman of Board (CB). This test further rules out an alternative explanation: the inside broker connection is capturing some unobserved and time-varying relationship between the firm and the brokerage that is not already ruled out by our falsification tests. Under this alternative, however, we should expect to find much weaker results when we restrict our sample to non-top insiders' Form 144 trades, as these non-top insiders are less likely to be in a position to influence the firm's investment banking (or other such important) relationships. Column (2) of Table 10 shows the results when the connect dummy is constructed only based on non-top insiders' Form 144 trades. For both the analyst and mutual fund setting, the results are economically and statistically similar to what we find using the full sample.

6.3 Defining Inside Brokers Based on Both Form 4 and Form 144 Trades

The third alternative sample we look at in this section is to combine both the Form 144 trades and Form 4 trades. Previous studies document that Form 4 trades are also informative; hence we should expect brokers to obtain an information advantage when processing Form 4 trades. Because the brokers used for Form 4 trades are not reported, we infer the broker identity based on the same insider's Form 144 trades and restrict the Form 4 trades to be within one year of Form 144 trades of the same insider. We then construct broker-affiliated analysts or funds using the extended sample and report the results in column (3) of Table 10. Our results still hold and are largely similar to those in our baseline in Tables 2 and 3.

7 Heterogeneity

In this section, we examine the circumstances under which the inside broker's information advantage is likely to be more useful. In order to save space, we briefly discuss our cross-sectional results here while relegating all further details to the IA (Section 4 in the IA, Tables IA.10 for affiliated analysts and IA.11 for fund managers).

First, our hypothesis is that broker-affiliated analysts/fund managers obtain non-public information on insider trades through their relationship with their colleagues at the brokerage's trading desks. However, an analyst/manager is likely to take some time to develop a good relationship with colleagues who interact with insider-clients. Hence we expect our results to be weaker when the affiliated analyst has joined the brokerage firm recently. This is what we find. In a similar vein, we next examine whether a connected analyst's/manager's information advantage is stronger when she is geographically co-located with their trading desk colleague, and therefore more likely to share a closer relationship with the latter. Again, we find consistent results.

Second, we examine career concerns. We find that our results are stronger for analysts facing more competition from other analysts on the same stock (stronger for higher analyst-coverage stocks, controlling for firm size). Analogously, our fund results are also stronger for managers facing more competition, that is, when managers are competing for family resources with many other managers. We also examine whether the effect of being connected depends on analyst/manager skill, proxied for using past performance. On the one hand, skilled analysts/managers may be in a better position to exploit the information advantage through inside brokers, because they can combine their unique insights with the additional information and generate more accurate forecasts. On the other hand, less-skilled analysts/managers who understand that they are not otherwise good at forecasting firm performance might be especially incentivized to exploit any information edge within their reach to improve their forecasts/trades. Our evidence supports the latter view, for both analysts and fund managers.

Next, we examine the strength of results partitioned on firm characteristics such as firm size, book-to-market ratio, return volatility, analyst forecast dispersion, turnover, analyst coverage, book-to-market ratio, and R&D intensity. We find that the information advantage of broker-affiliated analysts/fund managers is more pronounced among small firms, firms with high growth opportunity and return volatility, and firms with highly dispersed analyst and investor opinions. This is consistent with the view that any private information obtained in the process of facilitating insider transactions is more useful when there is more underlying uncertainty about the firm prospects. Finally, we examine trade characteristics that could indicate more informative insider trades. We find that larger and less frequent insider trades give a bigger edge to both broker-affiliated analysts and funds.

To conclude this section, many studies (e.g., Cohen, Frazzini and Malloy, 2010) find that Regulation Fair Disclosure (Reg FD) has effectively curbed the information advantage analysts enjoyed through access to management in the pre-Reg FD period. As a result, many analyst information-based effects are less significant in the more recent period. When we examine our effects separately for the pre-Reg FD and the post-Reg FD period, however, we find that our results are still relevant. These results are reported in Table 12 in the IA.

8 Conclusion

We use a form filed with the SEC to identify the stock broker that a firm insider trades through, and show that analysts and fund managers affiliated with such 'inside brokers' obtain a significant information advantage. These affiliated analysts' forecasts are significantly more accurate, and the affiliated fund managers' trades are more profitable than those of their competitors, especially in the period right after the insider trades through their brokerage. We design multiple strategies to test and assess these findings carefully and find consistent results throughout. These results contribute to our understanding of how stock brokers facilitate the transfer of valuable information from corporate insiders to market participants and suggest that information asymmetry arising from insider trading is not only restricted to the period before trade disclosure.

9 References

Bae, K.H., Stulz, R.M. and Tan, H., 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. Journal of Financial Economics, 88(3), pp.581-606.

Barbon, A., Di Maggio, M., Franzoni, F. and Landier, A., 2019. Brokers and order flow leakage: Evidence from fire sales. The Journal of Finance, 74(6), pp.2707-2749.

Bhattacharya, U. and Daouk, H., 2002. The world price of insider trading. The Journal of Finance, 57(1), pp.75-108.

Bradley, D., Gokkaya, S. and Liu, X., 2017. Before an analyst becomes an analyst: Does industry experience matter?. The Journal of Finance, 72(2), pp.751-792.

Chen, T. and Martin, X., 2011. Do bank-affiliated analysts benefit from lending relationships?. Journal of Accounting Research, 49(3), pp.633-675.

Chung, K.H. and Cho, S.Y., 2005. Security analysis and market making. Journal of Financial Intermediation, 14(1), pp.114-141.

Clement, M.B., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?. Journal of Accounting and Economics, 27(3), pp.285-303.

Cohen, L., Frazzini, A. and Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy, 116(5), pp.951-979.

Cohen, L., Frazzini, A. and Malloy, C., 2010. Sell-side school ties. The Journal of Finance, 65(4), pp.1409-1437.

Cohen, L., Malloy, C. and Pomorski, L., 2012. Decoding inside information. The Journal of Finance, 67(3), pp.1009-1043.

Coval, J.D. and Moskowitz, T.J., 2001. The geography of investment: Informed trading and asset prices. Journal of political Economy, 109(4), pp.811-841.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of finance, 52(3), pp.1035-1058.

Cvijanović, D., Dasgupta, A. and Zachariadis, K.E., 2016. Ties that bind: How business connections affect mutual fund activism. The Journal of Finance, 71(6), pp.2933-2966.

Di Maggio, M., Franzoni, F., Kermani, A. and Sommavilla, C., 2019. The relevance of broker networks for information diffusion in the stock market. Journal of Financial Economics, 134(2), pp.419-446.

Diether, K.B., Malloy, C.J. and Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. The Journal of Finance, 57(5), pp.2113-2141.

Geczy, C. and Yan, J., 2006. Who are the beneficiaries when insiders trade? An examination of piggybacking in the brokerage industry. An Examination of Piggybacking in the Brokerage Industry. Unpublished working Paper, Wharton.

Gormley, T.A. and Matsa, D.A., 2014. Common errors: How to (and not to) control for unobserved heterogeneity. The Review of Financial Studies, 27(2), pp.617-661.

Gormley, T.A. and Matsa, D.A., 2016. Playing it safe? Managerial preferences, risk, and agency conflicts. Journal of financial economics, 122(3), pp.431-455.

Green, T.C., Jame, R., Markov, S. and Subasi, M., 2014. Access to management and the informativeness of analyst research. Journal of Financial Economics, 114(2), pp.239-255.

Hong, H. and Kacperczyk, M., 2010. Competition and bias. The Quarterly Journal of Economics, 125(4), pp.1683-1725.

Hong, H. and Kubik, J.D., 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. The Journal of Finance, 58(1), pp.313-351.

Imbens, G. and Wooldridge, J., 2007. What's New in Econometrics?, NBER Summer Institute Lecture Notes, Lecture 10.

Lakonishok, J. and Lee, I., 2001. Are insider trades informative?. The Review of Financial

Studies, 14(1), pp.79-111.

McNally, W.J., Shkilko, A. and Smith, B.F., 2017. Do brokers of insiders tip other clients?. Management Science, 63(2), pp.317-332.

Malloy, C.J., 2005. The geography of equity analysis. The Journal of Finance, 60(2), pp.719-755.

Marin, J.M. and Olivier, J.P., 2008. The dog that did not bark: Insider trading and crashes. The Journal of Finance, 63(5), pp.2429-2476.

Massa, M. and Rehman, Z., 2008. Information flows within financial conglomerates: Evidence from the banks–mutual funds relation. Journal of Financial Economics, 89(2), pp.288-306.

Mayew, W.J. and Venkatachalam, M., 2012. The power of voice: Managerial affective states and future firm performance. The Journal of Finance, 67(1), pp.1-43.

Seyhun, H.N., 1986. Insiders' profits, costs of trading, and market efficiency. Journal of financial Economics, 16(2), pp.189-212.

Seyhun, H.N., 1998. Investment Intelligence from Insider Trading. MIT Press, Cambridge, MA.

Table 1: Summary Statistics

This table reports summary statistics for our sample. Panel A reports the number of observations, mean, 25th percentile, median, and 75th percentile for variables relevant to Form 144 trades. Multiple trades of the same insider on the same date are treated as one. We winsorize all the ratio variables at 1% and 99% level. In Panel B we report the summary statistics for the entire analyst forecast sample. Percentage absolute forecast error is the absolute value of actual EPS minus analyst forecasted EPS, scaled by stock price 12 months prior to the annual earnings announcement date (multiplied by 100). Percentage signed forecast error is the actual EPS minus analyst forecasted EPS, scaled by stock price and multiplied by 100. Connect is a dummy equal to 1 if the analyst issues an earnings forecast on a stock within one year after the firm's insiders trade through a brokerage firm employing this analyst. Forecast age is the natural log of the number of days between the forecast announcement date and earnings announcement date. Market capitalization is the firm's market value of equity 12 months before the earnings announcement date. Book-to-market ratio is the natural log of book value of equity over market value of equity ending in December. Volatility is the rolling standard deviation of the firm's past 36-month return. Forecast dispersion is the standard deviation of annual EPS forecasts, scaled by the absolute value of the average outstanding forecasts, following Diether, Malloy and Scherbina (2002). We remove the connected analysts' forecasts when calculating forecast dispersion. Analyst coverage is the natural log of one plus the number of analysts covering the firm at each fiscal year. Turnover is the monthly trading volume scaled by total shares outstanding, averaged over the past six months. Residual analyst coverage is the residual from the month-by-month cross-sectional regression of log(1+Analysts) on log (Size) and a Nasdaq dummy, following Hong, Lim and Stein (2000). R&D intensity is R&D expenses scaled by contemporaneous sales revenue. Analyst tenure is the number of years the analyst has worked at this brokerage house up to the current year. Number of firms covered is the number of firms the analyst followed in a given year. In Panel C, we report the summary statistics for sample when the connect dummy is equal to 1. Insider trade size is the average number of shares traded by connected insiders as a percentage of total shares outstanding. Number of trades is the total number of insider trades that occurred during the period from 1 year prior to the earnings announcement to the forecast announcement day for the connected forecast. In Panel D, we report the summary statistics for the pseudo-connect sample, defined as analyst-firm pairs that are connected at some point but not currently so (i.e., an insider traded through the brokerage employing this analyst in some other period but not in the current period). Panel E reports the summary statistics for the Compustat/CRSP merged sample. In Panel F, we report summary statistics for broker-affiliated mutual funds. Broker-affiliated mutual funds are defined as those mutual funds belonging to a family that is part of a financial conglomerate involving a brokerage house. Expense ratio is the annual expense ratio. Turnover is the minimum of aggregated sales or aggregated purchases of securities divided by the average twelve-month TNA of the fund. Manager tenure is the number of months since the manager took control of the fund. Panel G reports the summary statistics for the profitability following broker-affiliated mutual funds' trades on connected stocks. Signed return (%) is the quarterly stock return (in percentage) if a fund increases the weight of that stock in its portfolio from the previous quarter, and negative of the stock's quarterly return if the fund reduces that stock's weight. Fund's portfolio weight on a stock is defined as fund holdings in the stock (in dollar value) scaled by total portfolio value of the fund. [-5, +5] * quarterly returns (%) is defined as quarterly stock returns (in percentage) multiplied by a categorical variable ranging from -5 to +5. For all positive weight changes, we group them into 5 quintiles (from 1 to 5, with larger number indicating more positive portfolio weight changes). Similarly, for all negative portfolio weight changes, we group them into 5 quintiles (from -1 to -5, with smaller number indicating more negative portfolio weight changes).

Panel A: Form 144 trades

	No. of obs.	Mean	p25	Median	p75
# of insiders per company	11380	18	3	9	21
# of trades per company	11380	52	5	18	60
# of insiders per company-year	59462	6	1	3	7
# of trades per company-year	59462	10	2	5	11
# of shares traded per trade	591715	149676	3615	10036	34476
# of shares traded per trade (% of shares outstanding)	591715	0.112%	0.006%	0.026%	0.090%
Value of shares traded per trade	591508	3056155	67284	250620	889140
Value of shares traded per trade (% of market cap)	591508	0.114%	0.007%	0.026%	0.091%
# of shares traded per company-year	59462	1489446	25485	109382	393370
# of shares traded per company-year (% of shares outstanding)	59462	1.242%	0.099%	0.389%	1.248%
Value of shares traded per company-year	59452	30406714	287389	1633965	8461869
Value of shares traded per company-year (% of market cap)	59452	1.278%	0.099%	0.396%	1.271%
# of brokers used by different insiders of the firm	9803	4	2	3	6
# of brokers used by insiders with >=2 trades at the same firm	50135	1.2	1	1	1

Panel B: Full analyst forecast sample

Variables	No. of Obs.	Mean	p25	Median	p75
Percentage absolute forecast error	582183	1.18	0.05	0.16	0.54
Percentage signed forecast error	582183	-0.22	-0.09	0.03	0.21
Connect	600686	2.92%	0	0	0
Forecast age	600686	4.14	3.76	4.50	4.65
Market capitalization	516619	8836.63	457.65	1578.84	5730.99
Book-to-market ratio (ln)	496283	-0.93	-1.39	-0.84	-0.37
Volatility	579748	11.94%	6.80%	9.93%	14.67%
Forecast dispersion	540076	0.15	0.02	0.04	0.10
Turnover	554649	0.90%	0.32%	0.62%	1.13%
Analyst coverage	532758	2.39	1.95	2.48	2.94
Residual analyst coverage	532757	0.31	0.00	0.33	0.64
R&D intensity	264706	277.68%	0.47%	4.56%	14.72%
Analyst tenure	600686	4.31	2.00	3.00	6.00
No. of firms covered	599995	18	11	15	21

Panel C: Connected forecast sample

Variables	No. of obs.	Mean	p25	Median	p75
Percentage absolute forecast error	17240	0.68	0.03	0.11	0.35
Percentage signed forecast error	17240	-0.02	-0.03	0.03	0.17
Connect	17551	100.00%	1	1	1
Insider trade size	17570	0.20%	0.01%	0.03%	0.08%
No. of trades	17570	4.50	1.00	2.00	4.00
Market capitalization	16032	12907.83	759.33	2440.61	9081.80
Book-to-market ratio (ln)	14900	-1.21	-1.69	-1.11	-0.60
Volatility	17122	13.90%	7.35%	11.06%	17.28%
Forecast dispersion	16346	0.12	0.02	0.03	0.07
Turnover	16350	1.02%	0.44%	0.75%	1.26%
Analyst coverage	16322	2.48	2.08	2.56	3.00
Residual analyst coverage	16322	0.26	-0.05	0.28	0.57
R&D intensity	9473	386.64%	0.95%	9.12%	19.05%
Analyst tenure	17551	5.03	2.00	4.00	7.00
No. of firms covered	17539	16	11	16	20

Panel D: Pseudo-connect sample

Variables	No. of obs.	Mean	p25	Median	p75
Percentage absolute forecast error	28880	0.72	0.03	0.11	0.35
Percentage signed forecast error	28880	-0.05	-0.03	0.03	0.18
Connect	29964	0%	0	0	0
Market capitalization	27048	13011.54	974.23	3088.22	10039.90
Book-to-market ratio (ln)	25982	-0.99	-1.46	-0.93	-0.44
Turnover	27799	0.98%	0.40%	0.72%	1.25%
Analyst coverage	27707	2.57	2.20	2.71	3.04
Analyst tenure	29964	5.07	2.00	4.00	7.00
No. of firms covered	29930	17	12	16	21

Panel E: Compustat/CRSP sample

Variables	No. of obs.	Mean	p25	Median	p75
Market capitalization	43678	2993.95	65.19	271.05	1144.90
Book-to-market ratio (ln)	43667	-0.74	-1.25	-0.66	-0.15
Turnover	62824	0.62%	0.15%	0.37%	0.78%
Analyst coverage	64437	1.29	0.00	1.39	2.08

Panel F: Broker-affiliated mutual funds sample

	No. of obs.	Mean	P25	Median	P75
# of distinct stocks	1533				
# of brokers with affiliated funds	16				
# of affiliated funds per broker	16	13.4	3.5	8	25
Total Net Assets (TNA, millions of USD)	215	387.14	37.21	146.43	410.3
Expense ratio	215	1.43%	1.10%	1.37%	1.79%
Turnover	215	0.86	0.48	0.75	1.15
Manager Tenure (months)	215	68	29	57	98

Panel G: Profitability of Inside Broker-Affiliated Fund Trades

Variable	No. of obs.	Mean	p25	Median	p75
Connected Fund Sample					
Signed return (%)	168392	2.28	-9.47	1.99	13.63
[-5, +5] * quarterly returns (%)	168392	8.98	-32.70	6.17	49.61
Pseudo-Connect Fund Sample					
Signed return (%)	259820	0.86	0.00	0.00	0.00
[-5, +5] * quarterly returns (%)	259820	2.61	0.00	0.00	0.00

Table 2: Forecast Accuracy of Inside Broker-Affiliated Analysts

This table reports results for the sample of inside-broker affiliated analysts. The dependent variables are as follows. In columns 1-4, we examine Percentage Absolute Forecast Error (PAFE), which is the absolute value of an analyst's latest forecast, minus actual company earnings, as a percentage of stock price 12 months prior to the annual earnings announcement date. Target Price Error (column 5) is defined as |P12-TP|/P(-1), where P12 is the stock price 12 months following the target price release date, TP is the target price and P(-1) is the stock price 1 month before the target price release date. Most Accurate (column 6) is a dummy variable equals to one if the analyst's forecast is the most accurate among all analysts covering the same firm in the same year. Connect is a dummy equal to 1 if the analyst issues an earnings forecast on the stock within one year after a firm insider trades through the brokerage house employing this analyst. Forecast age is the natural log of the number of days between the forecast announcement and earnings announcement date. Inv. Bank Affiliation is a dummy equal to 1 if an analyst issues an earnings forecast on a stock within 1 year after its IPO or SEO date for which her brokerage firm is the lead underwriter. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	Percentage Absolute Forecast Error				Target Price Error	Most Accurate
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	-0.1540***	-0.0667***	-0.0794***	-0.0756***	-0.0203***	0.0243**
	(-5.53)	(-2.68)	(-2.92)	(-2.78)	(-3.36)	(2.03)
Forecast age				0.0506***		-0.0096***
				(6.00)		(-11.07)
Inv. Bank Affiliation				-0.1622	-0.0011	-0.0037
				(-1.43)	(-0.06)	(-0.85)
firm FE	yes	no	no	no	no	no
broker FE	yes	no	no	no	no	no
year FE	yes	no	no	no	no	no
firm-year FE	no	yes	yes	yes	yes	yes
analyst-broker-firm FE	no	yes	yes	yes	yes	yes
analyst-broker-year FE	no	no	yes	yes	yes	yes
Adj.R-sq	0.344	0.916	0.929	0.929	0.915	0.160
N.of Obs.	499459	383659	370578	370578	344178	399113

Table 3: Profitability of Inside Broker-Affiliated Fund Trades

This table examines the profitability of a trading strategy which follows broker-affiliated mutual fund trades. Broker-affiliated mutual funds are defined as mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. Fund's portfolio weight on a stock is defined as fund holdings in the stock (in dollar value) scaled by total portfolio value of the fund. In Columns 1-4, the dependent variable is Signed return, which is the quarterly stock return (in percentage) if a fund increases the weight of that stock in its portfolio from the previous quarter, and negative of the stock's quarterly return if the fund reduces that stock's weight. In Column 5, the dependent variable is quarterly stock returns (in percentage) multiplied by a categorical variable ranging from -5 to +5, which accounts for both the direction and magnitude by which the fund changes that stock's weight in its portfolio. To construct this variable, we group all stocks with positive weight changes into 5 quintiles (from 1 to 5, with larger numbers indicating more positive portfolio weight changes). Similarly, we group all stocks with negative weight changes into 5 quintiles (from -1 to -5, with smaller numbers indicating more negative portfolio weight changes). The independent variable of interest, Connect, is a dummy equal to one if a firm insider traded through a brokerage affiliated with this fund within 90 days before the end of quarter. All other variables are defined as in Table 2. All stocks that a fund held in some quarter but does not hold currently (conditional on the fund and stock existing) are counted as having zero portfolio weights in the current quarter. The panel regressions include fund-stock, fund-quarter, and stock-quarter fixed effects. The sample period is from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	Signed Return				Returns on a strategy based on trade direction and magnitude
	(1)	(2)	(3)	(4)	(5)
Connect	1.4340***	1.2435***	0.8574***	0.8931***	4.1232***
	(5.17)	(4.77)	(3.32)	(3.43)	(3.64)
Inv. Bank Affiliation				-0.0537	0.3470
				(-0.08)	(0.31)
firm FE	yes	no	no	no	no
fund FE	yes	no	no	no	no
quarter FE	yes	no	no	no	no
fund-stock FE	no	yes	yes	yes	yes
fund-quarter FE	no	no	yes	yes	yes
stock-quarter FE	no	yes	yes	yes	yes
Adj. R-sq.	0.013	0.132	0.146	0.146	0.127
No. of Obs.	51583403	51549911	51543399	51543399	51543399

Table 4: Timing of the Inside Broker Advantage

This table examines how the relative timing of forecasts/fund trades in relation to Form 144 trades affects results. Panel A reports results on broker-affiliated analyst forecast accuracy. Panel B reports results on the profitability of broker-affiliated fund trades. The dependent variables in these columns are PAFE and Signed return, as defined in Tables 2 and 3 respectively. In Panel A, we interact the Connect dummy with analyst forecasts made up to 90 days before insider trading date, forecasts made within 90 days following insider trading date, forecasts made between 90 and 180 days following insider trading date, and forecasts made more than 180 days following insider trading date. In Panel B, we interact the Connect dummy with mutual fund trades up to 90 days before insider trading date, fund trades within 90 days following insider trading date, fund trades between 90 and 180 days following insider trading date, and fund trades more than 180 days following insider trading date. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	Percentage Absolute Forecast Error
Connect up to 90 days before insider trades	0.0069
	(0.28)
Connect within 90 days following insider trades	-0.1287***
	(-2.68)
Connect between 90 and 180 days following insider trades	-0.0505*
	(-1.72)
Connect more than 180 days following insider trades	-0.0370
	(-1.22)
Forecast age	0.0509***
	(6.00)
Inv. Bank Affiliation	-0.1611
	(-1.42)
firm-year FE	yes
analyst-broker-firm FE	yes
analyst-broker-year FE	yes
Adj. R-sq.	0.847
No. of Obs.	370578

Panel B: Profitability of Broker-affiliated Mutual Fund Trades

	Signed Return
Connect up to 90 days before insider trades	0.0598 (0.32)
Connect within 90 days following insider trades	0.8677*** (3.34)
Connect between 90 and 180 days following insider trades	0.3326** (2.18)
Connect more than 180 days following insider trades	0.2435 (0.62)
Inv. Bank Affiliation	-0.0778 (-0.10)
fund-stock FE	yes
fund-quarter FE	yes
stock-quarter FE	yes
Adj. R-sq.	0.146
No. of Obs.	51543399

Table 5: Falsification Tests

This table reports results from three falsification tests. Panel A reports results on broker-affiliated analyst forecast accuracy, and Panel B reports results on the profitability of broker-affiliated fund trades. The dependent variables in these columns are PAFE and Signed return, as defined in Tables 2 and 3 respectively.

In columns (1) and (2), we examine insiders who switch to a different broker to execute their trades but continue working for the same firm. Specifically, we create a dummy "Pseudo connect" equal to 1 when the analyst (fund manager) at the no-longer-connected brokerage issues an earnings forecast (trades on the connected stock) within a year following the insider's trade through the new broker. In columns (3) and (4), we focus on cases where insiders change jobs, but retain their broker. Specifically, we create a dummy "Pseudo connect" equal to 1 when an analyst (fund manager) issues an earnings forecast (trades) on the previously connected firm following a trade by an unconnected insider at the same firm (who does not trade through this analyst/manager's brokerage) within one year of the connected insider leaving the firm. In columns (5) and (6), we consider an analyst (or fund manager) who continues to cover (hold) the same firm as he did for the inside broker, but now moves to a not-connected brokerage house (a brokerage house that does not facilitate trading for any insider at that firm). Specifically, we create a dummy "Pseudo connect" equal to 1 when such an analyst (manager) issues an earnings forecast (trades on the insider's firm) within one year following a firm insider's trade through the old broker (that the analyst/fund manager no longer works for). The sample period is from 1997 to 2013. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-Affiliated Analyst Forecast Accuracy

	Insider changes broker, but stays at the same firm		Insider changes job & other firm insiders trade through non-connected brokers		Analyst changes job, but covers the same firm	
	(1)	(2)	(3)	(4)	(5)	(6)
Pseudo connect	-0.0066	-0.0026	0.0192	0.0234	-0.0168	-0.0201
	(-0.22)	(-0.09)	(0.66)	(0.81)	(-0.37)	(-0.45)
Connect		-0.0673**		-0.0687***		-0.0674**
		(-2.56)		(-2.65)		(-2.56)
Inv. Bank Affiliation	-0.163	-0.1622	-0.1631	-0.1624	-0.163	-0.1622
	(-1.44)	(-1.43)	(-1.44)	(-1.43)	(-1.44)	(-1.43)
analyst-broker-firm FE	yes	yes	yes	yes	yes	yes
analyst-broker-year FE	yes	yes	yes	yes	yes	yes
firm-year FE	yes	yes	yes	yes	yes	yes
Adj. R-sq.	0.929	0.929	0.929	0.929	0.929	0.929
No. of Obs.	370578	370578	370578	370578	370580	370580

Panel B: Profitability of Broker-Affiliated Fund Trades

	Insider changes broker, but stays at the same firm		Insider changes job & other firm insiders trade through non-connected brokers		Fund manager changes job to a non-affiliated fund	
	(1)	(2)	(3)	(4)	(5)	(6)
Pseudo connect	-0.1133	-0.1116	-0.0799	-0.0810	0.1024	0.1034
	(-1.15)	(-1.08)	(-0.82)	(-0.84)	(1.12)	(1.15)
Connect		0.8524***		0.8439***		0.8413***
		(3.10)		(3.14)		(3.04)
Inv. Bank Affiliation	-0.0317	-0.0539	-0.0706	-0.0543	-0.0425	-0.0546
	(-0.05)	(-0.08)	(-0.09)	(-0.08)	(-0.06)	(-0.08)
fund-stock FE	yes	yes	yes	yes	yes	yes
fund-quarter FE	yes	yes	yes	yes	yes	yes
stock-quarter FE	yes	yes	yes	yes	yes	yes
Adj. R-sq.	0.146	0.146	0.146	0.146	0.146	0.146
No. of Obs.	51543399	51543399	51543399	51543399	51543399	51543399

Table 6: Tests Using Non-Major Brokers

This table reports results focusing on insider trades only through non-major brokers. We define a major broker as one used by more than 50% (column 1) or 25% (column 2) of insiders in a firm. The remaining brokers used by insiders are defined as non-major brokers. We then rerun our empirical tests using the sample of non-major brokers. Panel A reports results on broker-affiliated analyst forecast accuracy, and Panel B reports results on the profitability of broker-affiliated fund trades. The dependent variables in these columns are PAFE and Signed return, as defined in Tables 2 and 3 respectively. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	Major broker defined as those used by >50% of insiders in a firm	Major broker defined as those used by >25% of insiders in a firm
Connect	-0.0676**	-0.0643**
	(-2.36)	(-2.00)
Forecast age	0.0503***	0.0507***
	(5.91)	(5.92)
Inv. Bank Affiliation	-0.1858	-0.2004
	(-1.56)	(-1.59)
firm-year FE	yes	yes
analyst-broker-firm FE	yes	yes
analyst-broker-year FE	yes	yes
Adj. R-sq.	0.847	0.846
No. of Obs.	367412	364964

Panel B: Profitability of Broker-affiliated Mutual Fund Trades

	Major broker defined as those used by >50% of insiders in a firm	Major broker defined as those used by >25% of insiders in a firm
Connect	0.8782**	0.7899***
	(2.39)	(2.85)
Inv. Bank Affiliation	-0.0915	-0.0827
	(-0.12)	(-0.11)
fund-stock FE	yes	yes
fund-quarter FE	yes	yes
stock-quarter FE	yes	yes
Adj. R-sq.	0.146	0.146
No. of Obs.	51535852	51526001

Table 7: Major Broker's Information Advantage When Insider Trades Through Non-Major Broker

This table reports the regression results on the accuracy (profitability) of analysts (fund managers) affiliated with the firm's major broker when an insider trades through a different, non-major broker. We define major broker as a broker used by more than 50% (column 1) or 25% (column 2) of insiders in a firm. The remaining brokers used by insiders are defined as non-major brokers. Panel A reports results on broker-affiliated analyst forecast accuracy, and Panel B reports results on the profitability of broker-affiliated fund trades. The dependent variables in these columns are PAFE and Signed return, as defined in Tables 2 and 3 respectively. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	Major broker defined as those used by >50% of insiders in a firm	Major broker defined as those used by >25% of insiders in a firm
Connect	-0.0001	-0.0143
	(-0.00)	(-0.36)
Forecast age	0.0505***	0.0506***
	(5.94)	(5.88)
Inv. Bank Affiliation	-0.1877	-0.1487
	(-1.58)	(-1.22)
firm-year FE	yes	yes
analyst-broker-firm FE	yes	yes
analyst-broker-year FE	yes	yes
Adj. R-sq.	0.847	0.846
No. of Obs.	367412	364964

Panel B: Profitability of Broker-affiliated Mutual Fund Trades

	Major broker defined as those used by >50% of insiders in a firm	Major broker defined as those used by >25% of insiders in a firm
Connect	0.2488	-0.1192
	(1.36)	(-0.63)
Inv. Bank Affiliation	-0.0903	-0.0826
	(-0.12)	(-0.11)
fund-stock FE	yes	yes
fund-quarter FE	yes	yes
stock-quarter FE	yes	yes
Adj. R-sq.	0.146	0.146
No. of Obs.	51535852	51526001

Table 8: Tests Using Inside Brokers Only

This table reports the regression results of a test where we restrict the sample to those brokers who have at some point in time facilitated a trade by a firm insider. Panel A reports results on broker-affiliated analyst forecast accuracy, and Panel B reports results on the profitability of broker-affiliated fund trades. The dependent variables in these columns are PAFE and Signed return, as defined in Tables 2 and 3 respectively. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	PAFE
Connect	-0.0543**
	(-2.25)
Forecast age	0.0360***
	(3.35)
Inv. Bank Affiliation	-0.1701
	(-1.48)
firm-year FE	yes
analyst-broker-firm FE	yes
analyst-broker-year FE	yes
Adj. R-sq.	0.829
No. of Obs.	144924

Panel B: Profitability of Broker-affiliated Mutual Fund Trades

	Signed Return
Connect	0.8445***
	(3.24)
Inv. Bank Affiliation	-0.0257
	(-0.03)
fund-stock FE	yes
fund-quarter FE	yes
stock-quarter FE	yes
Adj. R-sq.	0.146
No. of Obs.	2389086

Table 9: Routine Insider Trades

Panel A of this table reports results on analyst forecasts around routine/non-routine Form 144 trades. In column (1), the dependent variable is the signed analyst percentage forecast error (PFE). In column (2), the dependent variable is PAFE, defined as in Table 2. Panel B of this table reports the results of broker-affiliated mutual fund trading around routine/non-routine Form 144 trades. In column (1), the dependent variable is a 'Positive/Negative change in portfolio weight' indicator that equals to 1 (-1) if a fund increases (reduces) its portfolio weight on the stock, and zero otherwise. Column (2) reports results of profitability of broker-affiliated fund trades around routine/non-routine insider trades. The dependent variable is Signed return, defined as in Table 3. Following Cohen et al. (2012), routine insider trades are those that occurred in the same calendar month for three consecutive years. "Connect 1st in sequence" is the interaction of the connect dummy with a dummy indicating a first-year routine trade. "Connect 2nd in sequence" is the interaction of the connect dummy with a dummy indicating a second-year routine trade. "Connect later in sequence" is the interaction of the connect dummy with a dummy indicating a routine trade in the third year or beyond. "Connect non-routine" is the interaction of the connect dummy with a dummy indicating non-routine insider trades. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-Affiliated Analyst Forecast

	Signed Forecast Error	PAFE
Connect 1st in sequence	0.1358**	-0.1044*
	(2.09)	(-1.67)
Connect 2nd in sequence	-0.0331	-0.0585
	(-1.60)	(-0.86)
Connect later in sequence	-0.0090	0.0201
	(-0.33)	(0.37)
Connect non-routine	-0.0053	-0.0692***
	(-0.26)	(-2.59)
Forecast age	-0.0658***	0.0507***
	(-7.50)	(6.00)
Inv. Bank Affiliation	0.1024	-0.1622
	(1.07)	(-1.43)
firm-year FE	yes	yes
analyst-broker-firm FE	yes	yes
analyst-broker-year FE	yes	yes
Adj. R-sq.	0.847	0.929
No. of Obs.	370578	370578

Panel B: Broker-Affiliated Fund Trades

	Positive/Negative change in portfolio weight	Signed Return
	(1)	(2)
Connect 1st in sequence	0.1023***	0.4548*
	(5.52)	(1.87)
Connect 2nd in sequence	0.0312	0.0232
	(1.03)	(0.09)
Connect later in sequence	-0.0128	-0.1535
	(-0.99)	(-0.56)
Connect non-routine	-0.1487***	0.8897***
	(-15.94)	(3.42)
Inv. Bank Affiliation	-0.0204	-0.0991
	(-1.15)	(-0.14)
fund-stock FE	yes	yes
fund-quarter FE	yes	yes
stock-quarter FE	yes	yes
Adj. R-sq.	0.121	0.146
No. of Obs.	51543399	51543399

Table 10: Alternative Samples

This table reports robustness tests for our main results using three alternative samples. Panel A reports results of broker-affiliated analyst forecast accuracy. Panel B reports results of profitability of broker-affiliated fund trades. Column (1) use the independent samples: the analyst sample is purged of broker-stocks in which affiliated mutual funds also trade; the mutual fund sample is purged of broker-stocks in which affiliated analysts also make earnings forecasts. Column (2) use only the Form 144 trades from non-top insiders, defined as those insiders who are not CEO, CFO, President or Chairman of Board. Column (3) defines connected analysts' forecasts and connected fund-trading using both Form 144 and Form 4 insider trades. Brokers used for Form 4 transactions are identified based on Form 144's broker by matching the Form 4 trade conducted by the same insider in the same firm within 1 year of his/her Form 144 trades. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	Analyst without MF	**Non-top Insiders**	**Both Form 4 and Form 144**
Connect	-0.0864**	-0.0636**	-0.0521**
	(-2.06)	(-2.40)	(-2.15)
Forecast age	0.0521***	0.0507***	0.0507***
	(5.89)	(6.01)	(6.01)
Inv. Bank Affiliation	-0.1843	-0.163	-0.1622
	(-1.40)	(-1.44)	(-1.43)
firm-year FE	yes	yes	yes
analyst-broker-firm FE	yes	yes	yes
analyst-broker-year FE	yes	yes	yes
Adj. R-sq.	0.845	0.847	0.847
No. of Obs.	362043	370578	370578

Panel B: Profitability of Broker-affiliated Mutual Fund Trades

	MF without Analyst	**Non-top Insiders**	**Both Form 4 and Form 144**
Connect	0.8126***	0.8897***	0.8190***
	(3.13)	(2.96)	(2.91)
Inv. Bank Affiliation	-0.0408	-0.0598	-0.0636
	(-0.05)	(-0.08)	(-0.08)
fund-stock FE	yes	yes	yes
fund-quarter FE	yes	yes	yes
stock-quarter FE	yes	yes	yes
Adj. R-sq.	0.143	0.146	0.146
No. of Obs.	50263874	51543399	51543399

Inside Brokers: Internet Appendix

September 2020

1 Return Predictability of Form 144 Trades

We use Form 144 trades in this paper, which have not been thoroughly studied in the literature. So we first conduct a test on the relationship between these trades and future stock performance. We find that Form 144 trades – which are all insider sales – are followed by significant negative returns. In Panel A of Table IA.2, we construct a calendar-time portfolio that shorts the stocks with Form 144 trades in the past one month and longs all other stocks. The portfolio is re-balanced monthly. We report both the equal-weighted and value-weighted monthly Carhart (1997) four-factor alphas. In Panel B, we run Fama-MacBeth regressions of next month returns on two different measures of Form 144 trades, controlling for other usual cross-sectional stock return predictors. Results are consistent. This suggests that Form 144 trades are indeed informative for future firm prospects.

2 Robustness of Analyst Forecast Tests

In this section, we conduct more robustness tests on our baseline regression results on analyst forecasts presented in Table 2 of the paper. We report these results in Table IA.3. First, we winsorize our dependent variable PAFE at different thresholds. In column (1), we winsorize PAFE at the 0.5% and 99.5% levels. In column (2), we winsorize PAFE at the 2% and 98% levels. As we can see, the coefficient on the connect dummy is always significantly negative, no matter what threshold we use to winsorize. In columns (3) and (4), we use the stock price one month and one quarter, respectively, prior to the earnings announcement date to scale absolute forecast error. Our results still hold. In the last robustness test, we add two more control variables: forecast frequency and firm-specific experience, which have been shown in the literature to affect analyst forecast accuracy. Forecast frequency is the number of forecasts issued by an analyst for a particular firm during the year ending five days before the current forecast. Firm-specific experience is the number of years the analyst has followed this firm relative to all other analysts who are currently following the same firm. As column (5) shows, our result does not change with these two additional controls.

In Table IA.4, we present results from a different type of robustness analysis. Here we use a fixed sample and redo our main analysis, showing that nothing changes substantially.

One problem with interpreting the superior forecast accuracy of connected analysts as indicative of superior information is that the aforementioned accuracy tests do not distinguish bias from informativeness. For example, connected analysts may be more accurate simply because they are less optimistic, rather than better informed.

We investigate this possibility by running the baseline panel regression replacing our PAFE measure with the percentage (signed, not absolute) forecast error (PFE). PFE is defined as the actual EPS minus forecasted EPS scaled by stock price. The more positive the PFE, the less optimistic the analyst forecast is. If broker-affiliated analysts become more accurate simply because they are less optimistic, we expect the coefficient on the connect dummy to be significantly positive. Table IA.5 reports the regression result. As we can see, the coefficient on the connect dummy is negative and insignificant, so the results do not support the alternative explanation that connected analysts are less optimistic.[1]

Next, we examine accuracy for forecasts on quarterly earnings per share. Our main tests on broker-affiliated analysts use forecasts on annual EPS in I/B/E/S, following the literature (e.g., Clement (1999), Malloy (2005), Hong and Kacperczyk (2010), Bradley, Gokkaya and Liu (2017), among others), as these are the most commonly issued types of forecasts. In this section, we show the results also obtain using forecasts on quarterly EPS. The dependent variable is percentage absolute forecast error PAFE, calculated using quarterly EPS forecasts and actual numbers.

Connect is a dummy equal to 1 if the analyst issues a quarterly earnings forecast on a stock within one quarter after the firm's insiders trade through a brokerage house employing this analyst. We require the insider trades to be within two adjacent quarterly earnings

[1]The coefficient on the affiliation dummy is also not significant. The literature documents that the affiliation status affects analysts' long-term growth forecast and recommendations, but not annual earnings forecast (Lin and McNichols (1998)), so our result is not inconsistent with the large literature documenting that investment-banking-affiliated analysts are more optimistic.

announcement dates. We control for an investment bank affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects in the regression. Table IA.6 reports the regression result. The coefficient of the connect dummy is significantly negative, with a magnitude similar to that in Table 2 using annual EPS forecast.

3 Robustness of Affiliated Fund Trading Results

We first focus on broker-affiliated funds' trading in the quarter following Form 144 trades, and compare it to non-affiliated funds' trading on the same stock in the same quarter. If affiliated funds benefit from the inside broker's unique information advantage in the insider trading process, we expect these funds' own trades, in turn, to generate abnormal returns. Specifically, following insider trades through a brokerage, if affiliated funds decrease (increase) holdings of the insider's stock relatively more than other funds, we should see negative (positive) subsequent returns on that stock. We refrain from analyzing the performance of the entire fund, because trading a few connected stocks profitably need not have a statistically discernable impact on overall fund performance.

We start in Table IA.7 Panel A by examining the direction of trades and find that, on average, inside broker-affiliated mutual funds sell more aggressively after the insider trades through their brokerage. Again, note that our framework does not make any clear prediction on whether the broker-affiliated funds should sell or buy after the connected insider trade, or whether they should be more or less aggressive about it. [2] To illustrate, consider the following example. Suppose an affiliated mutual fund manager obtains information through the insider's broker that a large insider sale that everyone else infers as bad news is in fact not so (e.g., a first-in-a-regular-sequence trade, as in Section 5 of the paper). In this case, she would choose not to change her earlier beliefs on the company, at a time when other unaffiliated fund managers might do so. The prediction that our framework does make is that the affiliated mutual fund manager's trades after her choice of action – or inaction – will be more predictive about what happens to that stock in the future than non-affiliated funds' trades. We now focus on testing this prediction.

To do so, we examine the return predictability of these connected stock trades as follows. First, we measure a mutual fund's trading on a stock as its percentage change of quarterly

[2] We still present these results as they are informative on the channel through which predictability arises, as we clarify below.

holdings on the stock. To take care of time-invariant stock-specific trading differences across funds (Busse, Tong, Tong, and Zhang, 2019), we need to measure a fund's abnormal trading in each stock. We define abnormal trading by a fund as the percentage change in holdings of a stock in the quarter following a Form 144 trade minus its change in holdings of the same stock in the quarter immediately before (when none of the firm insiders traded).[3] We then construct a calendar-time portfolio long in stocks associated with Form 144 trades in which affiliated funds' abnormal buying is more aggressive than their non-affiliated peers' in the same quarter. The strategy goes short in the stocks associated with Form 144 trades in which affiliated funds' abnormal selling is more aggressive than non-affiliated funds'. Stocks enter into these portfolios, which we weight equally, in the month following the reporting month of the mutual fund holdings (rdate in the Thomson Reuters S12 file), and are held for 3 months before re-balancing. We require each portfolio to contain at least 30 stocks by investing in the risk-free asset in periods when less than 30 stocks enters these portfolios.[4]

In Table IA.7 Panel B, we report the monthly abnormal returns to this long-short trading strategy. We see that the stocks on which broker-affiliated funds are more negative than non-affiliated funds do worse in the following quarter. The long-short portfolio generates an abnormal return of 43 to 58 bps per month. Columns (1) and (2) show that adjusting for risk factors using either the Fama and French (1993) three-factor model or the Carhart (1997) four-factor model does not affect results. In the third column, we use the characteristics-based benchmark of Daniel et al. (1997), and find an abnormal return of 43 bps per month with a t-stat of 3.5. In unreported results, we find similar results when we use the Fama and French (2015) five-factor model, the Hou, Xue and Zhang (2015) Q-factor model or the Stambaugh and Yuan (2017) mispricing-factor model.

Looking at the long and short legs of the strategy separately, we find that the abnormal returns come largely from the short leg, not the long leg. This suggests that broker-affiliated funds' negative information from insider trades is more valuable than their positive information. This asymmetry is not surprising given that Form 144 trades are all insider sales, and contain negative information on average, as we have documented previously. Notice, however, that since profits are strong only on the short leg, when the broker-affiliated fund is more negative than the prevailing consensus, one could argue that these results are also consistent with the view that short-sale frictions prevent participants from trading all nega-

[3] We assume mutual funds trade at the end of each quarter and require the insider trades to occur within 90 days but at least 3 days before the quarter end to make sure fund managers are aware of insider trading.

[4] Our results are not sensitive to the exact number of stocks we require in these portfolios.

tive information away. While we cannot completely rule this out, this seems less likely in the light of our results in Panel A, which suggest that affiliated funds do trade more aggressively when they have negative, rather than positive, information relative to their competitors; instead pointing towards the possibility that negative information is perhaps more valuable in the context of Form 144 sales. Also of note is that the stocks we consider are typically larger companies (a firm in the 25th percentile of our sample still has a market-cap of $759 million and is covered by 2 analysts). Such stocks are unlikely to have binding short-sales constraints.

One concern about the tests above could be that broker-affiliated funds are simply better at stock picking than non-affiliated funds. In that case, it would not be surprising that their trades are able to predict abnormal stock returns. In Panel C and D of Table IA.7, we conduct several tests to address this concern.

We first look at the performance of not-connected stocks traded by these broker-affiliated mutual funds in the same quarter as their trades on connected stocks. A typical broker-affiliated fund holds positions across many stocks, and only a few, if any, of these are connected through an inside brokerage relation. If the superior performance of broker-affiliated funds' trading on connected stocks comes from their general stock-picking skill – even time-varying stock-picking skill – we should find similar out-performance for these simultaneously not-connected stock trades as well. To test this, we construct a similar calendar-time long-short portfolio. The strategy goes long (short) in the not-connected stocks that the broker-affiliated funds buy (sell) more aggressively than their non-affiliated peers, measured at the same quarter as our baseline portfolio strategy (in which we looked at similar trading differences with connected stocks). We then examine the abnormal performance of this long-short portfolio. To clarify, then, this portfolio looks at the same affiliated funds' trading as our baseline, at the same time as their trading in connected stocks which we showed is predictive; but this time uses not-connected stocks only. Table IA.7, Panel C reports the results. We see that these portfolio abnormal returns are both magnitude- and significance-wise close to zero, regardless of the benchmark asset pricing models used.

In Panel D we examine affiliated funds' trades in stocks for which an insider traded through their affiliated brokerage in the past, but has not traded in recent times. We construct a long-short portfolio strategy similar to the one described above, based on differences in trading of once-affiliated funds and their never-affiliated peers. So, in this test, we keep the fund-stock pair the same, and look at the fund's performance on the once-connected stock in periods without an affiliated-broker-facilitated insider trading link. Again, results are both economically and statistically negligible. Finally, Panel E of the same table shows that defining the long/short signal based on simple trades, rather than abnormal trades, does not change our conclusions.

In Table IA.8, we report similar return predictability results in a HDFE regression setting. We construct two connect dummies capturing the trading of broker-affiliated funds relative to non-affiliated funds. Specifically, "Connect long" is a dummy which equals one for a stock associated with Form 144 trades in which the broker-affiliated funds' abnormal change of stock holding is larger than the non-affiliated funds' abnormal change of stock holding, and zero otherwise. "Connect short" is a dummy equals one if the broker-affiliated funds' abnormal change of stock holding is less than the non-affiliated funds' abnormal change of stock holding, and zero otherwise. We also construct a "Connect long-short" variable, which is defined as (Connect long – Connect short)/2. We assume mutual funds trade at the end of each quarter and require the insider trades to occur within 90 days but at least 3 days before the quarter end to make sure fund managers are aware of insider trading. We then run panel regression of quarterly stock return (in percentage) in quarter t ($Ret_{i,j,t}$) on the "Connect long" and "Connect short" dummy over the quarter $t-1$, and control for high-dimensional fixed effects at the level of fund-broker-quarter, fund-broker-stock and DGTW portfolio-quarter level. As mentioned previously in Section 3, these HDFEs follow the same structure as in analyst forecast test, except that now we cannot use firm x time FEs, and use portfolio characteristic (DGTW) FEs instead (Daniel et al., 1997).

We regress stock returns in quarter t ($Ret_{i,j,t}$) in the following setting:

$$Ret_{i,j,t} = \beta_1 + \beta_2 Connect\ long - short_{i,j,t-1} + paired\ HDFE + \epsilon_{i,j,t} \tag{1}$$

Column 1 shows that the coefficient on $Connect\ long - short$ is -1.34 (t=-5.35). Since we control for fund-broker-quarter fixed effect, the result cannot be explained by timing-varing fund trading skill. The inclusion of fund-broker-stock fixed effects help address the concern that broker-affiliated funds have persistent trading skill in certain stocks. With fund-stock fixed effects, we are comparing the fund's trading performance on the same stock in periods with and without an affiliated-broker-facilitated insider trading link.

Breaking this performance down, Column (2) shows that the coefficient on *Connect long* is 0.46 (t=1.99). Column (3) shows that the coefficient on *Connect short* is -1.17 and significant, implying that stocks on which broker-affiliated funds are more negative than non-affiliated funds underperform by 1.17% in the following quarter. This suggests that broker-affiliated funds' negative information obtained from insider trades is more valuable than their positive information. This asymmetry is not surprising, given that Form 144 trades are all insider sales, and contain negative information on average, as we have documented previously.

4 Timing of Inside Broker-Affiliated Analysts' Forecast Revision

In this section, we examine whether affiliated analysts issue new forecasts shortly after becoming more informed through the broker processing an insider trade. Although the earlier tables control for forecast vintage, if there was information flow, an analyst might want to update his or her forecast.[5] To test this hypothesis, we run a firm-broker-quarter panel regression. The dependent variable is a dummy indicating whether the broker had an updated forecast for that firm in that quarter. The independent variables are various time dummies measuring the time in quarters relative to insider trades from that firm. Specifically, *t-1* is a dummy variable that equals one in the quarter before the insider trade. We split the quarter in which the insider trades into the pre and post periods relative to the timing of the trade. *t0-pre* (*t0-post*) is a dummy that equals one for the period before (after) the insider trade within the quarter in which the insider trades. Similarly, *t1* and *t2* are time dummies that turn on one and two quarters, respectively, after the insider trade. *Connect* is a dummy that equals one for the analyst affiliated with the inside broker. Each of the time dummies is further interacted with the *connect* dummy to understand the differential propensity for the affiliated analyst to update her forecast following an insider trade through her brokerage. The results in Table IA.9 show that connected analysts are indeed more likely to issue a forecast than non-connected analysts in the same quarter of insider trades. However, they are no more likely than non-connected analysts to update forecasts in the quarter preceding or following that quarter. Even within the quarter of the insider trade, the affiliated analyst is significantly more likely to update her forecast after the insider trade, but not before it.

[5] Note, however, that it is not essential in our framework for the affiliated analyst to update her forecast after an insider trade. As an example, consider an insider trade that constitutes the beginning of a routine sequence (as in Section 3.4.3). After the insider trades, analysts not affiliated with the inside broker – who have no way yet to know that this trade will belong to a future sequence – might think this is an information-driven opportunistic trade. They might, therefore, revise their forecasts, while the affiliated analyst might retain hers.

5 Cross-sectional Heterogeneity

In this section, we examine the circumstances under which the inside broker's information advantage is likely to be more useful. All regressions relevant to this analysis are run with sub-sample indicators interacted with the connect dummy in Equation (1); they retain the structure of our baseline tests, including the HDFEs. Also, in our cross-sectional tests, we discuss all economic magnitudes with reference to the average PAFE in the relevant sub-sample, e.g., when we discuss differences in result magnitudes between small and large firm-samples, we benchmark the small-firm coefficient to the mean PAFE for analysts forecasting small-firm earnings.

5.1 Broker-Affiliated Analysts

Results for affiliated analysts are presented in Table IA.10.

5.1.1 Which Analysts?

Our hypothesis is that broker-affiliated analysts obtain non-public information on insider trades through their relationship with their colleagues at the brokerage's trading desks. However, an analyst is likely to take some time to develop a good relationship with colleagues who interact with insider-clients. Hence we expect our results to be weaker when the affiliated analyst has joined the brokerage firm recently. To test this, we create a dummy, *first-two-years* (*first-three-years*), indicating whether the analyst is within the first two (three) years of joining this brokerage firm, and interact it with the connect dummy.[6] These results are reported in the first four rows of Table IA.10, Panel A. Consistent with our hypothesis, the coefficient on the connect dummy is smaller in magnitude and not significant when the analyst has worked at her current firm for less than two or three years.

Next, we examine the number of stocks in the broker-affiliated analyst's coverage portfolio. On the one hand, the effect we document might be stronger when the connected analyst covers only a few – as opposed to many – stocks. First, Clement (1999) argues that analysts have deeper knowledge and insights on a specific firm when they have fewer stocks to

[6]For this test, we also control for the interaction between analysts' total years of experience with the connect dummy. This helps differentiate the effect of analyst's tenure at brokerage firm from the analyst's working experience.

cover. This type of expertise might also be crucial for a broker-affiliated analyst to correctly infer the information contained in insider trades. For example, if the broker learns from the telephone number that the connected CEO is calling from India to make a trade, only an affiliated analyst who knows that the firm is considering an acquisition in India might be able to infer its progress. Second, performance on one particular stock might matter more for an analyst's career if she covers — and gets evaluated on — a few stocks, rather than many. As a result, she might put a lot more effort in establishing connections with, and finding out information from, her colleagues in the brokerage division if the connected stock is one of a few she covers. On the other hand, while the above logic might hold for run-of-the-mill information, tips supplied by brokers might be unusual and more informative. Therefore, it is also possible that the number of stocks an analyst covers is unrelated to the analyst's responsiveness to inside information.

To empirically test these alternatives, we create a dummy *One-of-few*, equal to 1 when the number of stocks covered by an analyst is below that of the sample median analyst, and we interact it with the connect dummy. The results are reported in rows 5 and 6 of the panel. The coefficient on the *Connect one-of-few* dummy is -0.105 (t=-2.99), implying a 14.4% reduction in mean forecast error, while that on the *Connect one-of-many* (= 1 - *Connect one-of-few*) dummy is -0.054 (t=-1.66, a 7.3% reduction relative to the sample mean).

We also examine whether the effect of being connected on analyst forecast accuracy depends on analyst skill. On the one hand, skilled analysts may be in a better position to exploit the information advantage through inside brokers, because they can combine their unique insights with the additional information and generate more accurate forecasts. On the other hand, the improvement in forecast accuracy may be small for more skilled analysts because they tend to do well even without any advantage. Moreover, less-skilled analysts who understand that they are not otherwise good at forecasting earnings might be especially incentivized to exploit any information edge within their reach to improve upon their forecasts. To test this, we measure analyst skill as the percentile ranking of the analyst's forecast error on other firms relative to all other analysts following those firms in the same year. We then calculate the average ranking in terms of forecast error across all non-connected firms followed by the analyst in the previous year. The dummy variable *High skill* is equal to 1 if the analyst has a below-median ranking in terms of past forecast error. We then regress PAFE on the interaction term between the connect dummy and our analyst skill dummy, (rows 7 and 8 of Table IA.10, Panel A). Our result indicates that being affiliated with an inside broker is more useful for analysts with lower skill.

Our results rely on the connected analysts' information advantage coming from their interaction with trading desk colleagues who execute insider trades. To substantiate this assumption, we conduct a geography-based test. The idea is that an analyst who is geographically co-located with their trading desk colleague would perhaps have a closer relationship with the latter. To test this, we create a dummy *Same-location* equal to 1 if the analyst and the insider who trades through her brokerage firm are located in the same Metropolitan Statistical Area (MSA). We use the insider's location to approximate the broker's location since location information is available only for the insider, and the broker assigned by the brokerage firm is almost always located close to the trading client (which we verify by examining a 5% random sample of forms manually). We then regress PAFE on the interaction of the connect dummy and the *Same-location* dummy (rows 9 and 10 of Table IA.10, Panel A). The coefficient on the connect dummy is 3.5 times as large when the analyst and broker are from the same MSA, as compared to when they are not located in the same area. [7]

Finally, we examine residual analyst coverage, i.e., coverage orthogonal to firm size. We find that the economic magnitude of the connect dummy is larger in firms with high residual analyst coverage, although statistically, they are similar. This result is consistent with a competition effect: if we control for the information environment through firm size, there is more competition when more analysts cover the same stock (Hong and Kacperczyk, 2010). This strengthens incentives for the affiliated analyst to use all possible information to improve her forecast.

5.1.2 Characteristics of insiders' firms and trades

The first firm characteristic we look at is firm size. Small firms are less likely to be held by institutional investors and are followed by fewer analysts. Empirically, perhaps as a result

[7]In results we do not present here to save space, we show that this last test is not driven by the analyst being located close to the firm headquarters where the insider works. Prior literature has shown that local analysts have an information advantage not necessarily related to the channel we focus on (Malloy, 2005). While the analyst-firm fixed effects take this into account, if such an advantage arises especially at the times when insiders trade, this possibility is not ruled out by our main empirical design. Our evidence, however, assures us that this is not the case – the inside analyst's forecast remains more accurate than those of others when we focus on analysts co-located with insiders who do not reside where the firm is headquartered. For example, 52% of outside directors, and 73% of large shareholders, live outside the MSA where the firm is headquartered; their trades help us rule out this possibility.

of this, information diffusion speed is slower for smaller firms (Hong, Lim, and Stein, 2000). Previous research also documents that outsiders mimicking insider trades earn more profits in smaller firms (Lakonishok and Lee, 2001). We thus expect that the information obtained through the inside broker connection is more useful among small firms. This is what we find in the first two rows of Table IA.10, Panel B – our effect is stronger for small firms (coefficient of -0.17, t=-3.49, a 13.9% reduction relative to the sample mean), while the coefficient on *Connect big-firm* is close to zero.

Moreover, any private information obtained in the process of facilitating insider transactions could be more useful when there is more underlying uncertainty about the firms' prospects. To test this, we use two variables, stock return volatility and analyst forecast dispersion, to proxy for information uncertainty about firms' fundamentals. We again interact the connect dummy with a dummy indicating whether the firm has above or below median monthly return volatility or analyst forecast dispersion.[8] Return volatility results are reported in rows 3 and 4, and forecast dispersion results in rows 5 and 6, of Table IA.10, Panel B. Consistent with our hypothesis, we find that the coefficient on the connect dummy is indeed more pronounced for firms with more volatile stock returns or more dispersed analyst opinions. In the next two rows, we use monthly stock turnover to proxy for investors' (rather than analysts') difference of opinion (Hong and Stein, 2007). Again, we find the effect to be stronger for high turnover stocks.

Firms with lower analyst coverage tend to be less transparent, and information diffuses more slowly in such firms (Hong, Lim, and Stein, 2000). In rows 9 and 10 of Table IA.10, Panel B, we regress PAFE on the interaction between connect and another dummy indicating above or below median analyst coverage. The inside broker advantage is more pronounced among firms with lower analyst coverage, as expected. Next, we consider the hypothesis that firms with low book-to-market ratios have higher growth opportunities, for which information asymmetry is typically assumed to be higher than that for assets in place. So we expect inside information to be particularly useful for connected analysts among growth stocks. Similarly, firms with high R&D expenditures are inherently difficult to value, given the uncertainty associated with the innovation process (Aboody and Lev, 2000). Analysts who cover high R&D firms might benefit more from the inside broker connection. Our results are consistent with both hypotheses.

Finally, the broker-affiliated analysts' information advantage over other analysts crucially

[8] We leave out the connected analysts' own forecasts when calculating the analyst forecast dispersion measure.

depends on how informative the insider trade is for future firm value. The insider trading literature has documented that larger, less frequent insider trades are typically more informative (Bettis, Vickrey, and Vickrey, 1997; Cohen, Malloy, and Pomorski, 2012). Consistent with this, irrespective of whether we examine the frequency of insider trades or the size of the insider trade as a fraction of total shares outstanding, we find that these more informative insider trades give a bigger edge to the affiliated analysts.

5.2 Broker-Affiliated Mutual Funds

Table IA.11 presents cross-sectional differences in results for our sample of broker-affiliated funds. In Panel A, we examine the strength of results across different types of fund managers. First, we split the sample into two based on the number of other managers working in the same fund family. Managers who face more internal competition from other managers are likely to have a greater incentive to seek and exploit an inside broker advantage. Our result is indeed stronger for funds facing competition from other funds within a family (rows 1 to 2). Second, fund managers with longer tenure (two years or more in the family) are more likely to have established a stronger relationship with the broker through whom they get the information about the nature of the insider's trade. Consistent with this, we find stronger results for fund managers who have spent more time in the same fund company (rows 3 to 4). Rows 5 and 6 show that the benefits of being connected with an inside broker is larger when the fund manager has poorer performance over the past 12 months. This is perhaps because such managers with poorer performance have a stronger incentive to exploit additional information to improve performance. The last two rows in Panel A show that our results are more pronounced when the affiliated fund manager and broker are located in the same MSA, as compared to when they are not located in the same area, again indicating that geographic proximity to the inside broker helps.

In Panel B of Table IA.11, we examine the strength of results partitioned on firm characteristics including firm size, book-to-market ratio, return volatility, analyst forecast dispersion, turnover, analyst coverage, book-to-market ratio, and R&D intensity. Similar to Section 5.1, we find that the information advantage of broker-affiliated mutual funds is more pronounced among small stocks, stocks with high growth opportunity and return volatility, and stocks with highly dispersed analyst and investor opinions. Finally, we examine characteristics that could indicate more informative insider trades in the last four rows of Panel B, Table IA.11. We find that larger and less frequent insider trades give a bigger edge to the broker-affiliated mutual funds, again, consistent with our analyst results.

6 Pre-Regulation Fair Disclosure vs. More Recent Period

After the passage of Regulation Fair Disclosure (henceforth Reg FD) in year 2000, firm managers are not allowed to selectively disclose material non-public information to analysts and large institutional investors. Indeed, many studies (e.g., Cohen, Frazzini and Malloy, 2010) find that Reg FD has effectively curbed the information advantage analysts enjoyed through access to management in the pre-Reg FD period. As a result, analyst-related effects are weaker in the more recent period in many studies. We examine our effects in two subperiods, pre-Reg FD and the more recent period, in Table IA.12, Panel A. The *connect post-Reg FD* (*connect post-Reg FD* refers to forecasts issued after the year 2001) interaction has a coefficient of -0.097 (t=-2.95, a 11.3% reduction relative to the sample mean), indicating that our results are still relevant in more recent times. Similarly, Panel B of Table IA.12 in the IA shows that in the affiliated mutual fund context, we get consistent results.

7 Legality: A discussion

One natural question is whether the effect we document implies some illegal behavior. We consider this question from three different perspectives: i) Regulation Fair Disclosure (Reg FD), ii) fiduciary duty of the broker to her client, and iii) insider trading laws.

Reg FD does not apply in this context because it applies when "an issuer, or any person acting on its behalf, discloses any material nonpublic information regarding that issuer or its securities."[9] In our context, the information is in relation to a personal transaction that is incidentally transferred to the broker. Since the insider here is not acting on behalf of the issuer, Reg FD does not apply.

Next, we consider the perspective of the duty that the broker has towards her client (the insider who is trading). While there are clear rules (e.g. FINRA Rule 5270) that disallows use of the knowledge for client trade for frontrunning, that does not apply in this context, if the broker uses knowledge related to the trade of the client after the trade has been executed

[9] Source: https://www.ecfr.gov/cgi-bin/text-idx?amp;node=17:4.0.1.1.4&rgn=div5

and even made public. A different rule that could be relevant is FINRA Rule 2060, which governs the use of information obtained in a fiduciary capacity. It says "A member who in the capacity of paying agent, transfer agent, trustee, or in any other similar capacity, has received information as to the ownership of securities, shall under no circumstances make use of such information for the purpose of soliciting purchases, sales or exchanges except at the request and on behalf of the issuer." Our context does not seem to be in direct violation of this rule either.

Finally, we consider the perspective of insider trading. The general principle with regard to insider trading laws is that it disallows directly or indirectly benefiting from trading on material non-public information. Therefore, whether the behavior we document is illegal depends on two questions: (i) whether the analyst/fund manager obtained material non-public information, and (ii) whether the analyst/fund manager selectively disclosed it or traded on it to her own benefit. In our context, the information that the analyst obtains by talking to the broker of the insider may or may not be material. Broadly speaking, a piece of information is "material" if it would cause a reasonable investor to make a buy or sell decision. For example, information that a company is not doing well and is likely to announce large losses later in the year would be considered material. However, the SEC does not prohibit the disclosure of a non-material piece of information, even if, "that piece helps the analyst complete a "mosaic" of information that, taken together, is material."[10] For example, consider a case where it is publicly known that a company plans to expand internationally, but the countries where it plans to expand are not known. Suppose that the broker of the insider learns that the insider is making frequent trips to China. By talking to the broker, the analyst or the fund manager guesses – correctly – that the company is likely to launch its products in China. This information is not necessarily material, because even if this information were given to an investor, she may not know whether this is good news or bad, and therefore, whether she should buy or sell the stock. On the other hand, if the analyst obtains this information, she can spend more time and resources doing research on the likely demand for the company's products in China. As a result, she could gain a valuable information advantage about the future prospects of the company that is publicly known at that time. Doing so would not be illegal. Finally, disclosing that a trade is liquidity driven when the market does not know this is likely to be considered material since it is clear that a reasonable investor would know the direction she should trade in if she had this piece of information.

[10]Source: https://www.sec.gov/rules/final/33-7881.htm

Even if the information obtained by the analyst or the fund manager is material, e.g., that the company is likely to announce large losses for the year, the behavior of the analyst we document may not necessarily be illegal, per se. If the analyst does not herself trade on this information and discloses it for the first time in her publicly disseminated report, then there is nothing illegal about it. This is because whenever someone does come into possession of material non-public information, public disclosure of that information absolves her of any legal liabilities, at least with regard to insider-trading related issues.

On the other hand, if the analyst comes into possession of information that is considered material, and before making this information public, she tips off certain selective clients (e.g., Irvine et al. (2007)) or her in-house fund manager who then trade on this information to their benefit, this would be considered a tipping chain. This is illegal if every link in the chain knew that the previous person in the chain had violated her fiduciary duty when she passed on the information, if the information was material and non-public, and if she deliberately trades on or passes this information further to obtain some (even non-monetary) benefit. [11]

In case of the fund manager, if the information she obtains is material and she trades based on it, that would indeed be illegal. There is, however, an exception. The fund manager could obtain information about a large insider sale, which is observed by everyone and likely to be construed as bad news, but is in fact not so (e.g., a first-in-a-regular-sequence trade). In this case, she would choose not to sell her holdings in the company when other fund managers are doing so. Although the information, in this case, is material, using it to not trade is, in fact, not considered illegal according to the current laws.

Our earlier results, however, show that when the affiliated fund managers sell connected stocks more than others, the stock subsequently underperforms. Since the information is being exploited by the managers by selling more relative to others, any specifically identifiable

[11] In the SEC v. Obus case the Second Circuit Court clarified the elements of tipper/tipee liability. It held that tipper liability requires that: "(1) the tipper had a duty to keep material non-public information confidential; (2) the tipper breached that duty by intentionally or recklessly relaying the information to a tippee who could use the information in connection with securities trading; and (3) the tipper received a personal benefit from the tip." Tippee liability requires that: "(1) the tipper breached a duty by tipping confidential information; (2) the tippee knew or had reason to know that the tippee improperly obtained the information (i.e., that the information was obtained through the tipper's breach); and (3) the tippee, while in knowing possession of the material non-public information, used the information by trading or by tipping for his own benefit." Source: https://corpgov.law.harvard.edu/2012/09/26/second-circuit-clarifies-standards-for-insider-trading-claims/.

instance of this general behavior would be considered illegal according to the current laws.

Even if not all of our results necessarily imply illegal behavior, they do point to an information advantage for the inside broker. As discussed earlier, the possibility of other illegal activities remains, and warrants – at the very least – attention from insider trading law enforcement agencies.

8 References

Aboody, D. and Lev, B., 2000. Information asymmetry, R&D, and insider gains. *Journal of Finance* 55(6), pp.2747-2766.

Bettis, C., Vickrey, D. and Vickrey, D.W., 1997. Mimickers of corporate insiders who make large-volume trades. Financial Analysts Journal, 53(5), pp.57-66.

Bradley, Daniel, Sinan Gokkaya, and Xi Liu, 2017, Before an analyst becomes an analyst: Does industry experience matter? *Journal of Finance* 72(2), 751-792.

Busse, J.A., Tong, L., Tong, Q. and Zhang, Z., 2019. Trading regularity and fund performance. *The Review of Financial Studies*, 32(1), pp.374-422.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52(1), 57-82.

Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27(3), 285-303.

Cohen, L., Frazzini, A. and Malloy, C., 2010. Sell-side school ties. The Journal of Finance, 65(4), pp.1409-1437.

Cohen, L., Malloy, C. and Pomorski, L., 2012. Decoding inside information. The Journal of Finance, 67(3), pp.1009-1043.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. "Measuring mutual fund performance with characteristic-based benchmarks." *The Journal of Finance* 52, no. 3 (1997): 1035-1058.

Fama, Eugene F., and Kenneth R. French. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics* 33, no. 1 (1993): 3-56.

Fama, Eugene F., and Kenneth R. French. "A five-factor asset pricing model." *Journal of Financial Economics* 116, no. 1 (2015): 1-22.

Hong, H. and Kacperczyk, M., 2010. Competition and bias. The Quarterly Journal of Economics, 125(4), pp.1683-1725.

Hong, Harrison, and Jeffrey D. Kubik. "Analyzing the analysts: Career concerns and biased earnings forecasts." *The Journal of Finance* 58, no. 1 (2003): 313-351.

Hong, H., Lim, T. and Stein, J.C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. The Journal of Finance, 55(1), pp.265-295.

Hou, Kewei, Chen Xue, and Lu Zhang. "Digesting anomalies: An investment approach." *The Review of Financial Studies* 28, no. 3 (2015): 650-705.

Irvine, Paul, Marc Lipson, and Andy Puckett. "Tipping." *The Review of Financial Studies* 20, no. 3 (2007): 741-768.

Lakonishok, J. and Lee, I., 2001. Are insider trades informative?. The Review of Financial Studies, 14(1), pp.79-111.

Lin, H. W., and M. F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25(1), 101-127.

Stambaugh, Robert F., and Yu Yuan. "Mispricing factors." *The Review of Financial Studies* 30, no. 4 (2017): 1270-1315.

Figure IA.1

144 1 d99455d144.htm FORM 144

OMB APPROVAL	
OMB Number:	3235-0101
Expires:	May 31, 2017
Estimated average burden hours per response	1.00

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549

FORM 144

NOTICE OF PROPOSED SALE OF SECURITIES
PURSUANT TO RULE 144 UNDER THE SECURITIES ACT OF 1933

SEC USE ONLY
DOCUMENT SEQUENCE NO.
CUSIP NUMBER
WORK LOCATION

ATTENTION: *Transmit for filing 3 copies of this form concurrently with either placing an order with a broker to execute sale or executing a sale directly with a market maker.*

1(a) NAME OF ISSUER *(Please type or print)*			(b) IRS IDENT. NO.		(c) S.E.C. FILE NO.	
Sun Communities, Inc.			38-2730780		1-12616	
1(d) ADDRESS OF ISSUER	STREET	CITY	STATE	ZIP CODE	(e) TELEPHONE NO. AREA CODE	NUMBER
27777	Franklin Road, Suite 200	Southfield	MI	48034	248	208-2500

2(a) NAME OF PERSON FOR WHOSE ACCOUNT THE SECURITIES ARE TO BE SOLD		(b) RELATIONSHIP TO ISSUER	(c) ADDRESS	STREET	CITY	STATE	ZIP CODE
John B. McLaren		Pres & COO	27777	Franklin Rd Suite 200	Southfield	MI	48034

INSTRUCTION: The person filing this notice should contact the issuer to obtain the I.R.S. Identification Number and the S.E.C. File Number.

3(a) Title of the Class of Securities To Be Sold	(b) Name and Address of Each Broker Through Whom the Securities are to be Offered or Each Market Maker who is Acquiring the Securities	SEC USE ONLY Broker-Dealer File Number	(c) Number of Shares or Other Units To Be Sold *(See instr. 3(c))*	(d) Aggregate Market Value *(See instr. 3(d))*	(e) Number of Shares or Other Units Outstanding *(See instr. 3(e))*	(f) Approximate Date of Sale *(See instr. 3(f))* (MO. DAY YR.)	(g) Name of Each Securities Exchange *(See instr. 3(g))*
Common stock, $0.01 par value	UBS Financial Services Inc. 32300 Northwestern Hwy, Suite 150 Farmington Hills, MI 48334		5,000	$312,250	54,546,434	11/12/2015	NYSE

INSTRUCTIONS:

1. (a) Name of issuer
   (b) Issuer's I.R.S. Identification Number
   (c) Issuer's S.E.C. file number, if any
   (d) Issuer's address, including zip code
   (e) Issuer's telephone number, including area code
2. (a) Name of person for whose account the securities are to be sold
   (b) Such person's relationship to the issuer (e.g., officer, director, 10% stockholder, or member of immediate family of any of the foregoing)
   (c) Such person's address, including zip code
3. (a) Title of the class of securities to be sold
   (b) Name and address of each broker through whom the securities are intended to be sold
   (c) Number of shares or other units to be sold (if debt securities, give the aggregate face amount)
   (d) Aggregate market value of the securities to be sold as of a specified date within 10 days prior to the filing of this notice
   (e) Number of shares or other units of the class outstanding, or if debt securities the face amount thereof outstanding, as shown by the most recent report or statement published by the issuer
   (f) Approximate date on which the securities are to be sold
   (g) Name of each securities exchange, if any, on which the securities are intended to be sold

Potential persons who are to respond to the collection of information contained in this form are not required to respond unless the form displays a currently valid OMB control number.

SEC 1147 (08-07)

Table IA.1: Sample Coverage of the Brokers

This table reports the summary statistics of the brokers used in this paper. In Panel A, we list the distinct brokers used in broker-affiliated analyst sample and Panel B lists the brokers used in broker-affiliated mutual fund sample. Column (1) reports the name of brokers, column (2) the total number of Form 144 trades through this broker, and column (3) the dollar value of trades (millions of US dollars) through this broker. Columns (4) and (5) show the fraction of Form 144 trades through this broker a percentage of total dollar value or number of Form 144 trades through all brokers that have research analysts (Panel A) or mutual funds (Panel B), respectively. The sample period is from 1997 to 2013.

Panel A: Brokers used for analyst sample

Broker	# of trades	value of trades (millions of USD)	Fraction (dollar value)	Fraction (# of trades)
CREDIT SUISSE FIRST BOSTON	21571	238883	17.7%	4.1%
DONALDSON LUFKIN & JENRETTE	8929	192509	14.2%	1.7%
MERRILL LYNCH	68351	127931	9.5%	13.1%
MORGAN STANLEY DEAN WITTER	47753	105652	7.8%	9.2%
GOLDMAN SACHS	20552	101319	7.5%	3.9%
SALOMON SMITH BARNEY	42554	77559	5.7%	8.2%
J P MORGAN SECURITIES	19390	54322	4.0%	3.7%
UBS	34093	48852	3.6%	6.5%
DEUTSCHE BANK ALEX BROWN	33998	52415	3.9%	6.5%
BANK OF AMERICA	9665	29117	2.2%	1.9%
A G EDWARDS & SONS	26801	25160	1.9%	5.1%
PRUDENTIAL SECURITIES	4728	19694	1.5%	0.9%
BEAR STEARNS & CO	7424	15154	1.1%	1.4%
PAINE WEBBER	9293	10705	0.8%	1.8%
HAMBRECHT & QUEST	8886	9107	0.7%	1.7%
ROBERTSON STEPHENS & CO	6836	5349	0.4%	1.3%
ROBERT W BAIRD & CO	4707	4638	0.3%	0.9%
PIPER JAFFRAY	5586	4343	0.3%	1.1%
WELLS FARGO	3331	4337	0.3%	0.6%
RBC CAPITAL MARKETS	3963	4149	0.3%	0.8%
DAIN RAUSCHER	5533	8586	0.6%	1.1%
MORGAN KEEGAN & CO	2839	2398	0.2%	0.5%
RAGEN MACKENIZE	342	962	0.1%	0.1%
IJL WACHOVIA	853	786	0.1%	0.2%
EVEREN SECURITIES	650	717	0.1%	0.1%
INTERSTATE /JOHNSON LANE	859	789	0.1%	0.2%
J C BRADFORD & CO	757	661	0.0%	0.1%
WESSELS ARNOLD & HENDERSON	232	280	0.0%	0.0%
FIRST ALBANY	548	256	0.0%	0.1%
PRINCIPAL FINANCIAL SECURITIES	49	13	0.0%	0.0%
BANKERS TRUST CO	6	1	0.0%	0.0%
Total	401079	1146643	84.8%	76.9%

Panel B: Brokers used for mutual fund sample

Broker	# of trades	value of trades (millions of USD)	Fraction (dollar value)	Fraction (# of trades)
CREDIT SUISSE FIRST BOSTON	21571	238883	22.1%	4.4%
MERRILL LYNCH	68351	127931	11.8%	14.0%
CHARLES SCHWAB	32179	23458	2.2%	6.6%
FIDELITY	23550	23619	2.2%	4.8%
MORGAN STANLEY DEAN WITTER	46878	105255	9.7%	9.6%
GOLDMAN SACHS	20552	101319	9.4%	4.2%
SALOMON SMITH BARNEY	42554	77559	7.2%	8.7%
J P MORGAN SECURITIES	19390	54322	5.0%	4.0%
UBS	34093	48852	4.5%	7.0%
DEUTSCHE BANK ALEX BROWN	23805	39232	3.6%	4.9%
PRUDENTIAL SECURITIES	4728	19694	1.8%	1.0%
BEAR STEARNS & CO	7424	15154	1.4%	1.5%
HAMBRECHT & QUEST	8886	9107	0.8%	1.8%
ROBERTSON STEPHENS & CO	6836	5349	0.5%	1.4%
ROBERT W BAIRD & CO	4707	4638	0.4%	1.0%
WELLS FARGO	3331	4337	0.4%	0.7%
Total	368835	898710	83.0%	75.5%

Table IA.2: Return Predictability of Form 144 Trades

This table reports the return predictability of Form 144 trades. In Panel A, we construct a calendar-time portfolio that goes short on the stocks with Form 144 trades in the past one month and goes long on all other stocks. The portfolio is re-balanced monthly. We report both the equal-weighted and value-weighted monthly Carhart (1997) four-factor alpha. In Panel B, we run Fama-MacBeth regressions of next month stock return on 2 different measures of Form 144 trades, controlling for other cross-sectional stock return predictors. In column (1), Form144 sell dummy is an indicator equals 1 when the stock is associated with any Form 144 trades and zero otherwise. In column (2), the key predictor is Ln(1+# of Form144 sells) in the month. Ln(Market capitalization) is the natural log of the firm's market capitalization at the end of the June of each year. Book-to-market ratio is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum is defined as the cumulative returns from month t-12 to t-2. The lagged 1-month return is to capture short-term reversal effect. The sample period is from 1997 to 2013. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Full sample calendar-time portfolio

	Form144 Stocks	Other Stocks	Others - Form144
		Equal-weighted Portfolio	
FFC 4-factor alpha	-0.36%***	0.12%	0.48%***
t-stat	(-2.74)	(0.90)	(4.14)
		Value-weighted Portfolio	
FFC 4-factor alpha	-0.35%***	0.09%	0.44%***
t-stat	(-2.77)	(0.74)	(3.93)

Panel B: Fama-MacBeth Regression

	(1)	(2)
Ln(Market Capitalization)	-0.0013*	-0.0013*
	(-1.77)	(-1.76)
Book-to-market ratio	0.0009	0.0009
	(1.04)	(1.03)
Lagged 1-month return	-0.0337***	-0.0337***
	(-4.81)	(-4.81)
Momentum	0.0000	0.0000
	(0.00)	(0.00)
Form144 sell dummy	-0.0028**	
	(-2.30)	
Ln(1+# of Form144 sells)		-0.0026**
		(-2.26)
Constant	0.0169**	0.0168**
	(2.57)	(2.56)
Adj.R-sq	0.032	0.032
N.of Obs.	1094876	1094876

Table IA.3: Robustness of Analyst Forecast Tests

This table reports various robustness tests for the analyst forecast accuracy. In column (1), we winsorize the percentage absolute forecast error (PAFE) at the 0.5% and 99.5% levels. In column (2), we winsorize the percentage forecast error (PAFE) at the 2% and 98% levels. In column (3) and (4), we use the stock price one month and one quarter before earnings announcement date, respectively, to scale absolute forecast error. In column (5), we add two additional control variables. Forecast frequency is the number of forecasts issued by an analyst on a firm during the year ending five days before the current forecast. Firm-specific experience is the number of years the analyst has followed this firm relative to that of all other analysts who are currently following the same firm. The sample includes 600,686 earnings forecasts from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1) Winsorize at 0.5%	(2) Winsorize at 2%	(3) Last month price	(4) Last quarter price	(5) Additional controls
Connect	-0.0982**	-0.0435***	-0.2546***	-0.1672***	-0.0692**
	(-2.44)	(-2.72)	(-2.59)	(-2.71)	(-2.53)
Forecast age	0.0644***	0.0428***	0.1035***	0.0795***	0.0492***
	(4.33)	(8.51)	(4.60)	(5.15)	(4.25)
Inv. Bank Affiliation	-0.3298*	-0.0835	-0.8012**	-0.5438**	-0.1619
	(-1.72)	(-1.25)	(-2.19)	(-2.16)	(-1.41)
Forecast frequency					-0.0061
					(-1.34)
Firm-specific experience					0.0017
					(0.07)
firm-year FE	yes	yes	yes	yes	yes
analyst-broker-firm FE	yes	yes	yes	yes	yes
analyst-broker-year FE	yes	yes	yes	yes	yes
Adj. R-sq	0.943	0.923	0.953	0.950	0.930
No. of Obs.	370672	370672	381745	382552	364922

Table IA.4: Forecast Accuracy of Inside Broker-Affiliated Analysts (Fixed Sample)

This table reports results of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy. In column (1), we control for firm, brokerage, and year fixed effects. In column (2), we control for firm-year and analyst-broker-firm fixed effects. In column (3), we control for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. In column (4), we control for an Inv. Bank Affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects. All variable definitions appear in Table 2. The sample includes 600,686 earnings forecasts from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1)	(3)	(4)	(5)
Connect	-0.1725***	-0.0603**	-0.0712***	-0.0756***
	(-5.83)	(-2.56)	(-2.71)	(-2.78)
Forecast age				0.0506***
				(6.00)
Inv. Bank Affiliation				-0.1622
				(-1.43)
firm FE	yes	no	no	no
broker FE	yes	no	no	no
year FE	yes	no	no	no
broker-firm FE	no	no	no	no
firm-year FE	no	yes	yes	yes
analyst-broker-firm FE	no	yes	yes	yes
analyst-broker-year FE	no	no	yes	yes
Adj. R-sq	0.330	0.916	0.929	0.929
No. of Obs.	370578	370578	370578	370578

Table IA.5: Forecast Accuracy vs. Optimism

This table reports the panel regression of the signed percentage analyst forecast error (PFE) on the connect dummy. We control for an Inv. Bank Affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects All variable definitions appear in Table 2. The sample includes 600,686 earnings forecasts from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1)
Connect	-0.0028
	(-0.14)
Forecast age	-0.0659***
	(-7.50)
Inv. Bank Affiliation	0.1026
	(1.07)
analyst-broker-firm FE	Yes
analyst-broker-year FE	Yes
firm-year FE	Yes
Adj. R-sq	0.886
No. of Obs.	370578

Table IA.6: Forecast Accuracy of Inside Broker-Affiliated Analysts using Quarterly Earnings Forecast

This table reports results from panel regressions of percentage absolute forecast error for quarterly earnings forecast (PAFE) on the connect dummy. Connect is a dummy equal to 1 if the analyst issues an earnings forecast on a stock within one quarter after the firm's insiders trade through a brokerage firm employing this analyst. We require the insider trades to be within two adjacent quarterly earnings announcement dates. We control for an Inv. Bank Affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects. All variables definitions appear in Table 2. The sample includes 1,684,787 quarterly earnings forecasts from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1)
Connect	-0.0567**
	(-2.47)
Forecast age	0.0692***
	(8.37)
Inv. Bank Affiliation	-0.1599**
	(-1.97)
firm-year FE	yes
analyst-broker-firm FE	yes
analyst-broker-year FE	yes
Adj.R-sq	0.723
N.of Obs.	1255534

Table IA.7: Profitability of Inside Broker-affiliated Fund Trades: Calendar-time Portfolios

This table reports return predictability results based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds on stocks associated with Form 144 trades. Broker-affiliated mutual funds are defined as mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house.

Panel A reports the change of holding of broker-affiliated mutual funds relative to non-affiliated funds on Form 144-trade stocks following these trades. Panel B reports the monthly returns and alphas to a calendar-time long/short strategy. The strategy goes long in the stocks associated with Form 144 trades in which the broker-affiliated funds' abnormal change of quarterly holding is larger than the non-affiliated funds' abnormal change of quarterly holding. The strategy goes short in the stocks associated with Form 144 trades in which the broker-affiliated funds' abnormal change of quarterly holding is less than the non-affiliated funds' abnormal change of quarterly holding. Abnormal change of holding is defined as the change of holding in the quarter of Form 144 trades minus the change of holding of the same fund on the same stock in the quarter immediately before where none of the firm insiders traded. Panel C reports return predictability results based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds on non-connected stocks in the same quarter as Form 144 trades for connected stocks. The strategy goes long in the non-connected stocks in which the broker-affiliated funds' abnormal change of quarterly holding is larger than the non-affiliated funds' abnormal change of quarterly holding in the same quarter as Form 144 trades. The strategy goes short in the non-connected stocks in which the broker-affiliated funds' abnormal change of quarterly holding is less than the non-affiliated funds' abnormal change of quarterly holding in the same quarter as Form 144 trades. Panel D reports return predictability results based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds on connected stocks in quarters without Form 144 trades. The strategy goes long in the connected stocks in which the broker-affiliated funds' abnormal change of quarterly holding is larger than the non-affiliated funds' abnormal change of quarterly holding in quarters without Form 144 trades. The strategy goes short in the connected stocks in which the broker-affiliated funds' abnormal change of quarterly holding is less than the non-affiliated funds' abnormal change of quarterly holding in quarters without Form 144 trades. Panel E reports return predictability results based on the straight trading of broker-affiliated funds relative to non-affiliated funds on connected stocks. The strategy goes long in the stocks associated with Form 144 trades in which the broker-affiliated funds' change of quarterly holding is larger than the non-affiliated funds' change of quarterly holding. The strategy goes short in the stocks associated with Form 144 trades in which the broker-affiliated funds' change of quarterly holding is less than the non-affiliated funds' change of quarterly holding. All portfolios are equally weighted and are held for 3 months after the change of quarterly holding is reported. We require each portfolio to contain at least 30 stocks and invest in risk-free assets in periods of less than 30 stocks. Reported are the monthly Fama-French three-factor alpha (Fama and French, 1993), the Carhart (1997) four-factor alpha, and the DGTW-adjusted returns for the full sample (Daniel et al., 1997). The sample period is from 1997 to 2013. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Trading of broker-affiliated funds and non-affiliated funds following Form 144 trades

	Affiliated MF	**Non-affiliated MF**	**Affiliated-Not-affiliated**
Change of Holdings	-0.03%*** (-13.46)	-0.02%*** (-30.93)	-0.01%*** (3.62)

Panel B: Following the broker-affiliated fund trades in connected stocks

	3-factor alpha	4-factor alpha	DGTW adjusted
Long	-0.20%	-0.12%	0.11%
	(-1.13)	(-0.71)	(0.43)
Short	-0.71%***	-0.70%***	-0.32%***
	(-3.54)	(-3.45)	(-2.59)
Long-Short	**0.51%*** **	**0.58%*** **	**0.43%*** **
	(2.81)	**(3.19)**	**(3.50)**

Panel C: Following broker-affiliated fund trades in not-connected stocks at the same time

	3-factor alpha	4-factor alpha	DGTW adjusted
Long-Short	**-0.06%**	**-0.08%**	**-0.03%**
	(-0.91)	**(-1.17)**	**(-0.65)**

Panel D: Following broker-affiliated fund trades in connected stocks in periods without any inside-broker connection

	3-factor alpha	4-factor alpha	DGTW adjusted
Long-Short	**-0.04%**	**-0.05%**	**0.04%**
	(-0.26)	**(-0.29)**	**(0.25)**

Panel E: Following straight (not abnormal) trading of broker-affiliated Funds

	3-factor alpha	4-factor alpha	DGTW adjusted
Long-Short	**0.44%** **	**0.50%** **	**0.45%*** **
	(2.25)	**(2.56)**	**(2.58)**

Table IA.8: Profitability of Inside Broker-Affiliated Fund Trades: Panel Regressions with HDFE

This table reports return predictability results based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds on stocks associated with Form 144 trades. Broker-affiliated mutual funds are defined as mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. The dependent variable is quarterly stock returns (in percentage) and the independent variables are the "Connect long" and "Connect short" dummies. "Connect long" is a dummy variable equals one if the broker-affiliated funds' abnormal change of stock holding is larger than the non-affiliated funds' abnormal change of stock holding, and zero otherwise. "Connect short" is a dummy variable equals one if the broker-affiliated funds' abnormal change of stock holding is less than the non-affiliated funds' abnormal change of stock holding, and zero otherwise. "Connect long-short" is defined as (Connect long – Connect short)/2. Abnormal change of stock holding is defined as the change of stock holding in the quarter of Form 144 trades minus the change of holding of the same fund on the same stock in the quarter immediately before where none of the firm insiders traded. The sample period is from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
Connect long-short	1.3372***		
	(5.35)		
Connect long		0.4564**	
		(1.99)	
Connect short			-1.1708***
			(-6.49)
fund-broker-stock FE	yes	yes	yes
fund-broker-quarter FE	yes	yes	yes
DGTW portfolio-quarter FE	yes	yes	yes
Adj.R-sq	0.396	0.396	0.396
N.of Obs.	2398488	2398488	2398488

Table IA.9: Timing of Inside Broker-Affiliated Analysts' Forecast Revision

This table reports the timing of inside broker-affiliated analysts' forecast revisions around Form 144 trades. The dependent variable is a dummy variable indicating whether the broker had an updated forecast for that firm in that quarter. The independent variables are various timing dummies measuring the time in quarters relative to the recent insider trades from that firm. Specifically, t-1 is a dummy variable equals one when there are insider trades from that firm in the next quarter. t0-pre (t0-post) is a dummy variable equals one when there are insider trades in the same quarter and the analyst issues a forecast before (after) insider trades. Similarly, t1 and t2 are timing dummies equal to one when there are insider trades one and two quarters ago, respectively. Connect is a dummy variable equals one for the broker connected to the firm through insider trades. Each of the timing dummies is further interacted with the Connect dummy. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)
Connect*t-1	-0.0011	-0.0016*
	(-1.43)	(-1.91)
Connect*t0-pre	0.0009	0.0006
	(0.78)	(0.46)
Connect*t0-post	0.0115*	0.0228***
	(1.92)	(2.86)
Connect*t1	-0.0015	-0.0004
	(-0.99)	(-0.23)
Connect*t2	-0.0013	-0.0010
	(-0.68)	(-0.46)
t-1		-0.0083***
		(-6.84)
t0-pre		-0.0246***
		(-18.49)
t0-post	0.0925***	0.0826***
	(34.21)	(16.78)
t1		-0.0065***
		(-4.48)
t2		-0.0018
		(-1.13)
firm*quarter	yes	no
broker*quarter	yes	yes
broker*firm	yes	yes
firm*year	no	yes
Adj.R-sq	0.438	0.168
N.of Obs.	5123299	5261192

Table IA.10: Cross-sectional Tests: Broker-affiliated Analysts

Panel A reports results from panel regressions of PAFE, as defined in Table 1, on the connect dummy interacted with various analyst characteristics. In rows 1 and 2, "Connect first-two-years" ("Connect beyond-two-years") is the interaction of the connect dummy with a dummy indicating that the analyst is within (beyond) the first two years of joining the brokerage firm. In rows 3 and 4, "Connect first-three-years" ("Connect beyond-three-years") is the interaction of the connect dummy with a dummy indicating that the analyst is within (beyond) the first three years of joining the brokerage firm. For these two tests, we control for the interaction of the connect dummy with analyst's total years of experience. In rows 5 and 6, "Connect one-of-many" ("Connect one-of-few") is the interaction of the connect dummy with a dummy indicating that the number of stocks covered by the analyst in a year is above (below) sample median. In rows 7 and 8, "Connect high-skill" ("Connect low-skill") is the interaction of the connect dummy with a dummy indicating that the analysts' average ranking of forecast accuracy is above (below) median. In rows 9 and 10, "Connect same-location" ("Connect different-location") is the interaction of the connect dummy with a dummy indicating whether the analyst is located in the same MSA as the broker (but different MSA as the firm's headquarter). In rows 11 and 12, "Connect high-residual-coverage" ("Connect low-residual-coverage") is the interaction of the connect dummy with a dummy indicating the firm has above (below) median residual analyst coverage. Panel B reports results from panel regressions of PAFE on the connect dummy interacted with various firm and insider trade characteristics. In the first 2 rows, "Connect small-firm" ("Connect big-firm") is the interaction of the connect dummy with a dummy indicating below (above) median firm market capitalization. In rows 3 and 4, "Connect high-volatility ("Connect low-volatility") is the interaction of the connect dummy with a dummy indicating above (below) median monthly stock return volatility. In rows 5 and 6, "Connect high-dispersion" ("Connect low-dispersion") is the interaction of the connect dummy with a dummy indicating above (below) median analyst forecast dispersion. In rows 7 and 8, "Connect high-turnover" ("Connect low-turnover") is the interaction of the connect dummy with a dummy indicating above (below) median monthly stock turnover. In rows 9 and 10, "Connect high-coverage" ("Connect low-coverage") is the interaction of the connect dummy with a dummy indicating above (below) median analyst coverage. In rows 11 and 12, "Connect growth" ("Connect value") is the interaction of the connect dummy with a dummy indicating below (above) median book-to-market ratio. In rows 13 and 14, "Connect high-R&D-intensity" ("Connect low-R&D-intensity") is the interaction of the connect dummy with a dummy indicating above (below) median R&D intensity. In rows 15 and 16, "Connect infrequent-trade" ("Connect frequent-trade") is the interaction of the connect dummy with a dummy indicating the total number of insider trades that occurred during the period when connect is one is less (more) than 5. In the last 2 rows, "Connect small-trade" ("Connect big-trade") is the interaction of the connect dummy with a dummy indicating below (above) median average trade size. All variables are defined as in Tables 1 and 2. We control for analyst-broker-firm, analyst-broker-time and firm-time fixed effects in the regressions. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Which broker-affiliated analysts are more accurate?

	(1)
Connect first-two-years	-0.0749
	(-1.21)
Connect beyond-two-years	-0.1302*
	(-1.80)
Connect first-three-years	-0.0838
	(-1.41)
Connect beyond-three-years	-0.1583*
	(-1.91)
Connect one-of-many	-0.0543*
	(-1.66)
Connect one-of-few	-0.1051***
	(-2.99)
Connect high-skill	-0.0417
	(-1.42)
Connect low-skill	-0.0982***
	(-2.81)
Connect same-location	-0.1851***
	(-2.69)
Connect different-location	-0.0529**
	(-2.04)
Connect high-residual-coverage	-0.1320**
	(-2.05)
Connect low-residual-coverage	-0.0585**
	(-2.25)

Panel B: Characteristics of insiders' firms and trades

	(1)
Connect small-firm	-0.1708***
	(-3.49)
Connect big-firm	-0.0014
	(-0.06)
Connect high-volatility	-0.1529***
	(-3.03)
Connect low-volatility	-0.0225
	(-1.01)
Connect high-dispersion	-0.1121***
	(-3.06)
Connect low-dispersion	-0.0286
	(-0.91)
Connect high-turnover	-0.1269***
	(-2.86)
Connect low-turnover	-0.0085
	(-0.42)
Connect high-coverage	-0.0413
	(-1.18)
Connect low-coverage	-0.1167***
	(-3.28)
Connect growth	-0.0955**
	(-2.32)
Connect value	-0.0404
	(-1.38)
Connect high-R&D-intensity	-0.1718***
	(-2.60)
Connect low-R&D-intensity	-0.0664**
	(-2.35)
Connect infrequent-trade	-0.0795***
	(-2.80)
Connect frequent-trade	-0.0508
	(-1.05)
Connect small-trade	-0.0454
	(-1.63)
Connect big-trade	-0.1166***
	(-2.98)

Table IA.11: Cross-sectional Tests: Broker-affiliated Mutual Funds

This table reports cross-sectional results on the profitability of broker-affiliated mutual fund trades. The dependent variable is Signed return, as defined in Table 1. In Panel A, the coefficients of interest are on the connect dummy interacted with various fund characteristics. In rows 1 and 2, "Connect one-of-many" ("Connect one-of-few") is the interaction of the connect dummy with a dummy indicating that the number of funds in the fund family is above (below) sample median. In rows 3 and 4, "Connect long-tenure" ("Connect short-tenure") is the interaction of the Connect dummy with a dummy indicating that the fund manager's tenure is above (below) sample median. In rows 5 and 6, "Connect good performance" ("Connect bad performance") is the interaction of the connect dummy with a dummy indicating that the fund performance over the past 12 months is above (below) sample median. In rows 7 and 8, "Connect same-location" ("Connect different-location") is the interaction of the connect dummy with a dummy indicating whether the fund is located in the same MSA as the broker (but different MSA as the firm's headquarter). In Panel B, the coefficients of interest are the connect dummy interacted with various firm and insider trade characteristics. In rows 1 and 2, "Connect small-firm" ("Connect big-firm") is the interaction of the connect dummy with a dummy indicating below (above) median firm market capitalization. In rows 3 and 4, "Connect high-volatility" ("Connect low-volatility") is the interaction of the connect dummy with a dummy indicating above (below) median monthly stock return volatility. In rows 5 and 6, "Connect high-dispersion" (Connect dispersion") is the interaction of the connect dummy with a dummy indicating above (below) median analyst forecast dispersion. In rows 7 and 8, "Connect high-turnover" ("Connect low-turnover") is the interaction of the connect dummy with a dummy indicating above (below) median monthly turnover. In rows 9 and 10, "Connect high-coverage" ("Connect low-coverage") is the interaction of the connect dummy with a dummy indicating above (below) median analyst coverage. In rows 11 to 12, "Connect growth" ("Connect value") is the interaction of the connect dummy with a dummy indicating below (above) median book-to-market ratio. In rows 13 and 14, "Connect high R&D intensity" ("Connect low R&D intensity") is the interaction of the connect dummy with a dummy indicating above (below) median R&D intensity. In rows 15 and 16, "Connect infrequent-trade ("Connect frequent-trade") is the interaction of the connect dummy with a dummy indicating the total number of insider trades that occurred during the period when the connect dummy is one is less (more) than 5. In the last two rows, "Connect small-trade" ("Connect big-trade") is the interaction of the connect dummy with a dummy indicating below (above) median average trade size. All variables are defined as in Tables 1 and 3. All regressions include fund-stock, fund-quarter and stock-quarter fixed effects. The sample period is from 1997 to 2013. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Which broker-affiliated funds trade more profitably?

	(1)
Connect one-of-many	1.2377**
	(2.29)
Connect one-of-few	0.7740***
	(2.80)
Connect long-tenure	0.9682***
	(3.45)
Connect short-tenure	0.5065
	(1.13)
Connect good-performance	0.6291*
	(1.74)
Connect bad-performance	0.9853***
	(3.20)
Connect same-location	1.2318***
	(3.06)
Connect different-location	0.6977**
	(2.37)

Panel B: Characteristics of insiders' firms and trades

	(1)
Connect small-firm	1.5600***
	(3.14)
Connect big-firm	0.7038**
	(2.53)
Connect high-volatility	1.3803***
	(3.07)
Connect low-volatility	0.6927**
	(2.45)
Connect high-dispersion	1.1659***
	(2.87)
Connect low-dispersion	0.7250**
	(2.49)
Connect high-turnover	0.9029***
	(3.22)
Connect low-turnover	0.5220
	(0.85)
Connect high-coverage	0.4253
	(0.70)
Connect low-coverage	0.9159***
	(3.42)
Connect growth	1.2636**
	(2.32)
Connect value	0.7686***
	(2.85)
Connect high R&D intensity	0.9569***
	(3.53)
Connect low R&D intensity	0.1296
	(0.21)
Connect infrequent-trade	1.0195***
	(3.43)
Connect frequent-trade	0.4769
	(1.20)
Connect small-trade	0.5774
	(1.48)
Connect big-trade	1.0138***
	(3.51)

Table IA.12: Before and After Regulation Fair Disclosure

Panel A of this table reports results of broker-affiliated analyst forecast accuracy. Connect pre-Reg FD (Connect post-Reg FD) is the interaction of the connect dummy with a dummy indicating the period before (after) Regulation Fair Disclosure. We include analyst-broker-firm, analyst-broker-year, and firm-year fixed effects in the regression. Panel B reports results of profitability of broker-affiliated fund trades. The dependent variable, Signed Return, is quarterly stock returns (in percentage) multiplied by a buy/sell indicator that equals 1 (-1) if a fund's change of portfolio weight on a stock is positive (negative) from the previous quarter, and zero otherwise. The independent variables of interest, Connect pre-Reg FD (Connect post-Reg FD), is the connect dummy interacted with a dummy indicating the period before (after) Regulation Fair Disclosure. We include fund-stock, fund-quarter, and stock-quarter fixed effects in the regression. All other variables are defined as in Table 2. Standard errors are clustered by firm, and t-statistics are reported below each estimate. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Broker-affiliated Analyst Forecast Accuracy

	(1)
Connect pre-Reg FD	0.0056
	(0.23)
Connect post-Reg FD	-0.0968***
	(-2.95)

Panel B: Profitability of Broker-affiliated Fund Trades

	(1)
Connect pre-Reg FD	0.8567
	(0.87)
Connect post-Reg FD	0.8575***
	(3.68)