Inside Brokers

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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 10–20% more accurate earnings forecasts, and affiliated funds trade the insider's stock much 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 unique position to exploit such an asymmetry.

JEL classification: G24, G30, G34, G38

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1 Introduction

Insiders, by definition, have favored access to private information about their firm, and a large body of literature shows that they benefit from trading on such information.[1] But if such insider trades become a substantial part of stock turnover, other uninformed traders face the risk of being adversely selected against, which affects their willingness to trade (Kyle (1985), Glosten and Milgrom (1985)). This is the theoretical motivation behind insider trading laws and other regulations that try to keep adverse selection concerns of market participants under control, for example through the public disclosure of insider trades within a short time window. Typically, much of the academic and policy discourse around this implicitly assumes that any information asymmetry generated through insider trading is only acute before trade disclosure. Regulators, therefore, are especially careful in monitoring any suspicious trading behavior during this short window. In this paper we focus on one group of people involved in insider trading – brokers facilitating insider trades – and show that at least this group enjoys an information advantage, arising from the trading process, that *continues well after the public disclosure of the trade itself.*

Our analysis focuses on two related yet distinct reflections of such an "inside broker" advantage.

First, we show that the equity analyst who covers the insider's firm at the insider's brokerage provides significantly more accurate earnings forecasts. In terms of economic magnitude, the inside broker-affiliated analyst issues 10–20% more accurate forecasts of annual earnings after the insider has traded through her brokerage. This accuracy is relative to that of other analysts issuing forecasts on the same firm at the same time, and even relative to her *own* forecast accuracy on the *same firm at other times* without insider trades.

Second, we find that mutual funds affiliated with such an inside broker also enjoy a significant information advantage when they trade the insider's company shares. A portfolio trading strategy that goes long (short) on the connected insider's stock when the affiliated fund has bought (sold) that stock significantly more than their peers following a trade through their brokerage earns large abnormal returns. Again in terms of economic magnitude, these risk-adjusted returns are of the order of 55-60 basis points per month over the following quarter.

[1]See, for example, Lorie and Niederhoffer (1968), Jaffe (1974), Seyhun (1986, 1998), Rozeff and Zaman (1988), Lin and Howe (1990), Karpoff and Lee (1991), Bettis, Vickery and Vickery (1997), Lakonishok and Lee (2001), Bhattacharya and Daouk (2002), Marin and Olivier (2008), and Cohen, Malloy and Pomorski (2012).

Importantly, since these affiliated analysts' forecasts are issued – and fund managers' holdings are disclosed – *well after the occurrence of the insider trade itself becomes public knowledge* through SEC filings, our evidence suggests that not all of the inside broker's information advantage is dissipated by trade disclosure. The inside broker's information advantage, therefore, is both substantial and long-lived.

The plausibility of our narrative depends on affiliated analysts/mutual fund managers following publicly disclosed trades of insiders who trade through their brokerage division. Such a scenario is perhaps likely: when an analyst/fund manager realizes that a particular insider has traded through her firm, given her incentive to generate an information advantage, she might communicate with her broker colleague who interacted with the insider to glean something useful. For instance, the broker would know the nature of the trading instruction – was the order placed as a limit order a year in advance to be executed at the end of some particular month, or was it a quick market order placed right after a board meeting? The former kind of trade is obviously less likely to be information driven. However, market participants in general would never know whether the trade was through a limit or a market order, even after the insider trade is publicly disclosed. Many other channels could also endow the inside broker with a similar information advantage. To mention one more, the insider's personal broker might also know, for example, whether the sale of inside stock was accompanied by sales of *other*, unrelated stocks that the insider owns. This could help ascertain whether the trade was more likely due to liquidity reasons or information driven. Again, the rest of the market will never have this information.[2]

The key to this study is the identity of different insiders' brokers. We identify these brokers through SEC's Form 144, through which insiders are required to report certain types of stock sales (specifically, sales of restricted and control shares), as well as the broker used for each such transaction. We hand-match these brokerage names to I/B/E/S brokers to identify affiliated analysts, and separately to CRSP/ Thomson Reuters mutual fund names to ascertain affiliated mutual funds (broker-affiliated mutual funds as those that belong to a fund family that is part of a financial conglomerate involving a brokerage house, e.g., "Wells Fargo Small Cap Fund" is affiliated with Wells Fargo's brokerage).

The granularity of panel data available in these databases aids identification by allowing us to incorporate a rich set of fixed effects and placebo tests to rule out unobserved heterogeneity.[3] For example, in our tests using analyst forecasts, we can add fixed effects

[2] We list more such sources of the inside broker's information advantage in Section 6.

[3] Specifically, data granularity is at the firm - broker - analyst - time level for I/B/E/S, and the stock-

for every firm-time, broker-analyst-firm, and broker-analyst-time pair. The firm-time fixed effects control for the forecast accuracy of all analysts covering the firm at the same time and help account for the possibility that insider trades might precede periods during which it is easier to make more accurate earnings forecasts, or the possibility that all analysts are able to make better forecasts after observing a trade by an insider.

Since we can also include broker-analyst-firm fixed effects, the identification of our effect comes from earnings forecasts by a specific analyst at the insiders' broker showing higher accuracy in the period after the trade, relative to her *own forecasts on the same firm* in other periods. As a result, any omitted variable that is invariant at the broker-analyst-firm level (for example firm-specific analyst skill, or school ties between analysts and insiders (e.g., Cohen, Frazzini and Malloy, 2010)) does not affect our inference.

Additionally, broker-analyst-time fixed effects help control for time-varying analyst or brokerage level unobservables, such as analyst industry/sector experience, accuracy, or the possibility that in some years the brokerage is more resource constrained, which could affect the forecast accuracy of its analysts due to their inability to do adequate research.

We follow up these results on connected analyst accuracy with a series of placebo tests, each designed to rule out alternative explanations based on time-varying personal relationships or other types of unobserved (to the econometrician) business ties between the insiders' firm and the brokerage. Specifically, we consider breaks in the analyst-firm connection due to (1) analysts changing jobs, (2) insiders changing brokers, and (3) insiders changing jobs. In each case, we follow the analyst's performance in the period right after the connection breaks. None of these samples show any significant relation between forecast accuracy and insider trading – either in terms of statistical significance, or in terms of economic magnitude – revealing the imperativeness of the "inside broker" relationship.

Next, we use affiliated mutual fund trading to show complementary evidence. In our mutual fund tests, we first show that affiliated mutual funds trade more aggressively than other *competing mutual funds who also trade at the same time* in the insider's stock following the insider trade. While this in itself is not evidence of using information obtained through the inside broker connection, we further show that these affiliated trades are, on average, *predictive*: when affiliated mutual funds sell the connected stock much more heavily than their peers following the insider trade, the stock under-performs significantly. Overall, then, affiliated mutual funds seem to be actively exploiting their information advantage on the

(broker-affiliated) mutual fund - time level for Thomson Reuters.

insider's stock.

Second, we examine what happens to the future returns of other stocks *not connected through broker ties* that these same affiliated mutual funds trade at the same time as their connected stock. Our results show that these not-connected trades do not generate any abnormal future returns, unlike the connected trades. Since we are now comparing the same mutual fund's trade on other stocks *at the same time* as the connected trade, this rules out any fund-time alternatives, e.g., time-varying fund skill/attention/resources.

Finally, we also examine future stock return performance when the same affiliated mutual fund trades more aggressively on a stock to which they had an inside broker connection in the past, but are not currently connected; that is, previously connected stock trades in periods when the insider *did not trade through the affiliated broker*. Again we find no abnormal returns, ruling out fund-stock level unobserved heterogeneity – such as differences in trading profitability at the fund-stock level, which can arise for example from school ties between firm insiders and fund managers (Cohen, Frazzini and Malloy (2008)) or from information advantages from holding local stocks (Coval and Moskowitz (2001)).

We again follow this up with two placebo tests to rule out alternative explanations, using breaks in the fund-stock link through insiders changing their jobs or their brokers. Again, our placebo results are both economically and statistically insignificant.

While our results are robust across a variety of dimensions, not all firms are, of course, equally susceptible to the type of activity we document. In the cross-section, we find that the inside broker's information advantage is greater for firms whose stocks trade in a worse information environment: smaller, higher-return-volatility growth firms, those with higher dispersion of analyst forecasts, and those with higher R&D expenses. Examining different types of insider trades, we find that the advantage is greater following trades that are larger and less frequent. Finally, we also find evidence that in the cross-section of analysts/fund managers, those that have more pressing career concerns – for example due to higher competition – seem to be making more use of this advantage. Again, the robustness of these cross-sectional results is attested to by the fact that they are borne out across two very distinct types of tests in two different samples: one using analyst forecast accuracy, the other using affiliated funds' trading profitability.

Interestingly, unlike many other studies documenting analyst information advantages, we find that the advantage of the connected analyst exists only after Regulation Fair Disclosure (Reg FD). This could be because before Reg FD, analysts could have had preferential access to insiders through various direct-access channels. Following Reg FD, the relative advantage of the connected analyst, arising from her unique access to information due to her position at the insider's brokerage firm, goes up. We do not observe such a clear time difference in our mutual fund results.

In our final set of analyses, we return to the mechanism underlying our result and examine a specific but clean context in which we are able to demonstrate the precise nature of the connected analyst'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, have to be able to point out its existence from data observable to us, that is, from publicly available data.

One such candidate is a first-in-a-regular-sequence trade by an insider. Suppose an insider sells restricted stock every January. As Cohen, Malloy and Pomorski (2013) show, these regular trades are less likely to be information-driven. We conjecture that after observing the same insider trading at the same time over a few (say, three) consecutive years, all market participants will realize that such trades are part of a regular sequence and, hence, not information-driven. However, when the January trade happens *for the first time*, the typical outsider would not be able to foresee that this is going to be a regular and therefore uninformative occurrence. But the affiliated analyst and fund manager 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 weaken as the next-in-sequence trades start coming in. This is exactly what we observe in the data, again, both with affiliated analysts and mutual fund trades.[4]

This result on the inside broker's information advantage on first-in-a-regular-sequence trades also helps rule out a possible alternative explanation based on reverse causality. The reverse causality argument is that at certain points in time, the connected analyst/fund manager has some information or analysis advantage over everyone else – an advantage that does not have its source in the insider's trade. Naturally, at these times the affiliated analyst issues better forecasts and the affiliated fund manager trades more profitably on the insider's company. Crucially, these are also times when the insider's broker actually *recommends that the insider trade* in the same direction as the analyst/fund. In sum, the information advantage originates from the analyst or the fund manager and gets transmitted to the insider through her broker's trading recommendation. However, our first-in-a-regular-

[4]Of course, the inside broker also has significant information advantage on the irregular trades (i.e., those that are not in a sequence, and hence more likely to be informative), as one might expect.

sequence trade is an example of a trade which is not particularly informed about anything at the firm, yet the inside broker knows something more than the market. She knows that this is the start of a repeated trading pattern and hence is *not* information-driven. This is not a trading idea that could plausibly have originated from the affiliated analyst's or manager's superior information or analysis, so reverse causality cannot explain our result here.

Finally, although we focus on insider trades through brokers in this paper, what we uncover may have more general implications for the role played by such intermediaries. Our results here suggest a role for brokers as *information intermediaries*, not just mechanical facilitators of the trading process. Brokers might acquire an information advantage based on the nature of trading instructions or their interaction with clients – and *such clients may not just be firm insiders*. Brokers may also have many other avenues of asymmetric information advantages. To cite just a few, the broker might obtain a unique information advantage in knowing or inferring that an activist is gradually building stakes before a form 13D filing, or that a potential suitor is gradually building a toehold, or that a company founder is gradually selling his stake in the open market. Overall, then, we might just be touching upon the tip of the iceberg in this paper with respect to broker uniqueness.

The rest of the paper is organized as follows. Section 2 describes related literature, Section 3 details our data, Section 4 presents our main results on affiliated analysts and mutual funds, Section 5 presents cross-sectional evidence, Section 6 discusses some sources of the inside broker's information advantage, Section 7 discussed the legal implications of our findings, and Section 8 concludes.

2 Literature and our contribution

Our study contributes to the literature examining analysts' and fund managers' access to private information through their interactions with firm managers. For example, Coval and Moskowitz (2001) show that fund managers earn substantial abnormal returns in local investments, while Malloy (2005) and Bae, Stulz and Tan (2008) find that local analysts are more accurate than other analysts, suggesting that geographical proximity facilitates information flows. Cohen, Frazzini and Malloy (2008, 2010) document that fund managers and analysts who have an educational link to company management outperform others on their stock trades/recommendations. Green, Jame, Markov and Subasi (2014) find that access to management at broker-hosted investor conferences leads to more informative analyst research. While all of these studies indicate that selective disclosure from managers is an important source of information advantage, this paper focuses on flows of inside information into markets through a broker: a link not examined before, and of special interest in the regulatory context. Also, most of the earlier results, especially those with analysts, come from the pre-Reg FD period. In contrast, the information advantage connected analysts enjoy in our paper comes from their brokerage-affiliated insider trading activities, rather than direct access to management, and, perhaps as a result, lasts well after Reg FD (Table 9, Panel A). This means that our results are still topical and relevant to policy.

The second strand of literature our study contributes to is that on affiliated analysts and mutual funds. Lin and McNichols (1998) examine the effect of underwriting relationships on analysts' forecasting behavior. They show that analysts' growth forecasts and recommendations are significantly more favorable than those made by unaffiliated analysts, although their short-term earnings forecasts are not generally higher. Chung and Cho (2005) show that analysts cover stocks that are handled by affiliated dealers and issue optimistic reports on them to generate order flow. 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. Mola and Guidolin (2009) find that analysts issue favorable ratings on stocks that their affiliated mutual funds have invested in. In contrast to these papers, we not only look at a distinct channel, but also explicitly identify mechanisms by which a brokerage affiliation allows both analysts and fund managers to deliver superior performance (Section 6).

Our study is also related closely to papers that show brokers may be able to take advantage of their knowledge that an insider is trading. Geczy and Yan (2006) show that market makers who are also the brokers of insiders quote more aggressively on the day of the insider trade. However, this could also be consistent with inventory management by the market maker. MacNally, Shkilko and Smith (2015) show evidence that is consistent with brokers used by insiders in Canada engaging in tipping and insider trading on the same day as the insider trade. We make two main contributions relative to these papers.

First, the results of these papers imply that brokers have an information advantage *before* the public disclosure of the trade. Although interesting in its own right, this is perhaps not too surprising, and one might expect that such an information advantage would dissipate when the insider trade is revealed publicly. In contrast, our study shows that brokers retain an information advantage even well *after* the insider trade becomes public, which implies that some information beyond that contained in the trade disclosure itself passes to the inside broker. Information asymmetry arising from the insider trading process, therefore, is long-lived, contrary to what is typically assumed in many theoretical as well as empirical studies. Second, in the general setting of any insider trade used in these earlier papers, it is difficult to rule out reverse causality, which we can in this paper. The reverse causality hypothesis of concern in the literature is that it was the analyst at the inside broker, or the broker herself, who conducted analysis independently and recommended the trade to the insider and their other clients. If this were true, the data would show – as in this literature – that the inside brokers' clients trade more heavily in the direction of the insider trade than clients of other non-connected brokers in the pre-disclosure period. In this paper, we can rule out this possibility by specifically examining our subset of first-in-a-regular-sequence trades.

Finally, we show that there is significant and long-lived information gained by the broker facilitating insider trades, and that this results in more accurate affiliated analyst forecasts/more profitable affiliated fund trades. Consistent with our results on the broker's advantage, Di Maggio, Franzoni, Kermani, and Sommavilla (2017) uncover evidence of another distinct use of information by central brokers – involving the leakage of information gathered through execution of trades for their most important institutional clients.

3 Data

Insider trading data and information about the broker used by the insider are obtained from Form 144 files in the Thomson Financial Insider Trading database. This is a different source of information from Form 4, which is what most papers on corporate insider trading look at. We explain details about the background of regulations that require the filing of Form 144, and the nature of the information in these forms, in the Internet Appendix (IA). Moreover, Table 1 in the IA shows that insider sales reported on Form 144 are – on average – informative about future returns of the firm. We manually standardize broker names reported by different insiders and hand-match these names to I/B/E/S brokers.[5] Information about investment banks involved in security issuances is obtained from SDC Platinum database. Firm characteristics are obtained from the S&P Compustat database.

In Table 1 we present summary statistics for key variables used in our analysis. Our sample starts in 1997, which is the first year for which there is sufficient coverage of Form

[5]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.

144 data in the Thomson Financial Insider Trading database, and it ends in 2013. 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 median firm in our database has 9 distinct insiders who traded during the sample period. Trades have a median size of $250,620, while the mean is much larger and close to $3 million. In years when there is at least one trade, there is a median of five Form 144 trades, and they aggregate to a median of 0.4% of the company's shares outstanding. We present more details on these trades in Table 1, Panel A. The five most common brokers of insiders by number of trades are Merrill Lynch, Citigroup, Morgan Stanley, Paine Webber, and Deutsche Bank Alex Brown. In Panel B, we present summary statistics for the full sample of analysts, in Panel C for the sample of connected analysts, and in Panel D on forecasts made by connected analysts in periods where there is no connection (the pseudo-connect sample). In Panel E we present statistics on the Compustat variables we use, and in Panel F on analyst recommendation changes.

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 classes of the same fund by taking the TNA (total net assets) 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.

Panel G of Table 1 provides information on the broker-affiliated funds sample. Over the whole sample, our data contain 215 distinct funds involving 1533 unique stocks. We identify 16 distinct brokers with affiliated mutual funds, and these brokers each have 16 affiliated funds on average. The mean TNA of broker-affiliated funds is 387 million USD, and these funds have a mean annual expense ratio of 1.43% and a turnover ratio of 0.86. The bottom two rows of the panel report the monthly raw and net returns of broker-affiliated funds and non-affiliated funds. The monthly raw return is 0.65% and the net return is 0.54% for affiliated funds, which are very similar to the numbers for non-affiliated funds. This suggests that in general, affiliated funds are not more skillful than other funds. We measure mutual fund trading on a stock as the quarterly change in percentage of outstanding company shares held by a fund.

4 Main Results

4.1 Analysts employed at inside brokers

In this section, we investigate whether the analyst employed by the insider's brokerage firm has an information advantage over other analysts following trades by that insider. We do so by examining whether inside broker-affiliated analysts are more accurate in their forecasts in Section 4.1.1, and by looking at the profitability of trading on their recommendations around the next earnings announcements in Section **??**.

Note, however, that we deliberately do not explore the timing or magnitude of forecast or recommendation changes made by the inside analyst. This is because our framework makes no clear prediction about whether the connected analyst should update her forecasts/recommendations faster or more boldly after seeing a trade. To see this clearly, consider a connected analyst obtaining information through the insider's broker that a large insider sale – which is observed by everyone and likely to be construed as bad news – is in fact not so (e.g., a first-in-a-regular-sequence trade, as in Section 6). In this case, the analyst would choose not to change her forecast or recommendation on the company at all, at a time when other analysts might do so.[6] The only prediction from our framework is that her forecast after her choice of action – or inaction – following the trade will be more *accurate*; this is what we test.

Our main measure is analysts' scaled annual percentage absolute EPS forecast error (PAFE). We focus on annual earnings forecasts in I/B/E/S, following the literature (Lin and McNichols (1998), 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. 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 stock price 12 months prior to the actual earnings announcement date. The smaller the absolute forecast error, the more accurate the analyst's forecast.

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

We run panel regressions of PAFE on a connect dummy – our key explanatory variable,

[6] In addition, there might be another cost to updating immediately after every insider trade through one's own brokerage – that of attracting unnecessary regulatory scrutiny.

and control for various high-dimensional fixed effects (HDFE), such as those at the level of each stock-year, stock-analyst, and analyst-year.

$$PAFE_{i,j,t} = \beta_1 + \beta_2 Connect_{i,j,t} + \beta_3 Affil_{i,j,t} + \beta_4 Fore\_age_{i,j,t} + paired\_HDFE + \epsilon_{i,j,t} \quad (2)$$

The connect dummy is equal to 1 when the analyst issues an earnings forecast on a stock within a certain period after the firm's insiders trade through the brokerage house employing this analyst, and zero otherwise. *Affil* is an indicator for the parent of the brokerage house having an investment banking relationship with the insider's firm, and *Fore_age* controls for the vintage of the forecast to make sure that we distill our effect out from that of forecast recency.

4.1.1 Baseline results on forecast accuracy

In our baseline specification, we examine whether an analyst issues more accurate earnings forecasts on firms where at least one insider traded through the brokerage employing the analyst during that earnings year. One concern is that such connected analysts may be different in terms of other characteristics that correlate with forecast accuracy. For example, firm officers are more likely to trade through prestigious brokerage firms, and previous research documents that analysts employed by such brokerages are on average more accurate than those working in lower-tier brokerage houses (Clement (1999)). The effect of the connect dummy on forecast accuracy could then be due to a brokerage effect, rather than the information obtained through the insiders' broker. The common approach used by previous studies to mitigate such endogeneity concerns is to add various brokerage, analyst and firm characteristics that could be correlated with forecast accuracy. In this paper, we use a different approach that controls for a richer set of possibilities, including some not directly observable, using high-dimensional (interacted) fixed effects for brokerage, analysts, firm and year paired combinations. Our approach addresses endogeneity concerns more comprehensively because the controls employed by previous papers are absorbed by at least one of these paired fixed effects. Of course, our results are also robust to the more traditional approach taken in the literature of using a variety of control variables.

Table 2 reports these regression results. In column (1), we add firm, year and brokerage fixed effects. The coefficient on the connect dummy is -0.15 and highly significant (t=-5.53). This means that, consistent with our hypothesis, analysts are more accurate at forecasting a firm's earnings when one of that firm's insiders trades through the brokerage employing her during the past year. The economic magnitude of the increase in relative forecast accuracy for the connected analysts is also quite large. The mean of the percentage absolute forecast error (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 represents a 20.8% reduction in average forecast errors. In columns (2) and (3), we add paired fixed effects such as broker-firm and firm-year effects. The coefficient on the connect dummy is still significantly negative, although the magnitude is reduced by half. In column (4), we add a comprehensive set of paired fixed effects, including firm-year, analyst-broker-firm and analyst-broker-year effects. We still find the connect dummy to be significantly negative (t=-2.92). Connected analysts thus issue more accurate forecasts on the firms' annual EPS, compared to (i) all other analysts following the same firm in the current fiscal year, (ii) their own forecasts on other non-connected firms at the same time, and (iii) their own forecasts issued on the same firm during other periods when no firm insider traded through their brokerage firm.

One aspect of our data worth mentioning here concerns the statistical significance of our results given our large sample. While large samples typically allow for more precise estimation of effects, in our design we are essentially estimating the forecast accuracy of treated (inside-broker connected) stock-firm pairs minus control pairs. The number of treated pairs, even in our large sample, is understandably rare (2.92% of all observations, Table 1, Panel B). So, essentially, the control is being estimated very precisely in our case, because we have many control observations. But that cannot reduce the standard error in the estimate of the treatment group. Consequently, the standard error of the difference cannot go down beyond a particular point. Given this data structure, our treatment estimates are, if anything, surprisingly precise.

Although our pairs of firm-year, analyst-broker-year and analyst-broker-firm fixed effects capture most of the analyst, brokerage and firm characteristics that may correlate with the connect dummy and affect forecast error, there are still a couple of covariates that vary at the analyst-firm-time level, and are therefore not subsumed by these fixed effects. For example, prior studies (Clement (1999)) document that forecast age is a significant determinant of forecast accuracy, where forecast age is defined as log number of days from the forecast announcement day to the earnings announcement day. The literature finds that old forecasts are on average less accurate than more recent forecasts. In our case, it could be that connected analysts issue forecasts only after they see the insider trades, so it is possible that the age of connected forecasts is on average lower than that of non-connected ones. Another possibility is that firm managers use the same brokerage firm for underwriting their firm's shares and executing their own trades. Many papers (Lin and McNichols (1998), Hong and Kubik (2003)) find that analysts who cover stocks underwritten by their own brokerage houses forecast differently. Hence, our results could be driven by this underwriting affiliation rather than by brokerage-affiliated insider trading.

To alleviate these concerns, we add forecast age (*Fore_age*) and an affiliation dummy (*Affil*) indicating any underwriting relationship between the analyst and the covered firm in the regression. Specifically, the affiliation dummy is equal to 1 if the analyst issues an earnings forecast on a stock within 1 year after its IPO or SEO date for which her brokerage house is the lead underwriter for the IPO or SEO. Column (5) of Table 2 reports this result. First, we see that the coefficient on forecast age is significantly positive, consistent with the literature that older forecasts are less accurate. The coefficient on the affiliation dummy is negative but not significant.

More importantly, the connect dummy is not affected by adding these two additional controls. The coefficient on the connect dummy is -0.076 and significant at the 1% level. This coefficient means that connected analysts on average have a 10.5% smaller forecast error when the insider trades through their brokerage, even in this very stringent specification. 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 potential for information transmission, but does not allow us to exclude cases where there was no differential information transmitted in the trading process.

We do a variety of other tests to understand the robustness of our results, which we report in our Internet Appendix (IA). First, in Table 2 in the IA, we find that winsorizing our dependent variable PAFE at different thresholds, using stock prices one month or even 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) do not affect our results. Second, we show that even if we use a fixed sample so that we have the same number of observations across the columns of Table 3 to make the columns more comparable (Table 3 in the IA), 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 4 in the IA). Their optimism is similar to those without an inside broker connection; they are just more accurate.

Finally, we do further tests which show that the inside analysts' information advantage also extends to forecasting slightly more accurate target prices in the Internet Appendix, but the effect is much less pronounced than it is for short-horizon earnings forecasts, both economically and statistically.

4.1.2 Alternative Hypotheses and Falsification Tests

Our results so far are consistent with the hypothesis that inside analysts obtain information beyond that contained in the public disclosure of the insider trade itself, which they use to improve their earnings forecasts on the connected firm. Our use of a rich set of paired firm, analyst, broker and time fixed effects makes alternative explanations unlikely to explain our finding. However, this does not rule out the possibility that some time-varying versions of the alternative hypotheses we outlined earlier could be consistent with our result. For example, Cohen, Frazzini and Malloy (2010) find that analysts who have attended the same college as the firm managers have an information advantage on the connected firm when making recommendations. Since the school connection between the analyst and the insider is time-invariant, our analyst-firm fixed effect will capture any such effect if the information flow from insider to analyst is also stable over time. However, the information flow from the insider to the analyst may well be time-varying. An insider may have significant private information only in some periods, and it may be that it is in these periods that he both trades and communicates the information to his school friend the inside analyst. Our earlier tests are not specified to deal with such an issue.

Hence, to rule out such possibilities, and to show that the channel through which the inside analyst gets more accurate information is indeed contingent on *insiders trading through her brokerage*, we conduct three falsification tests. Specifically, we consider breaks in the analyst-firm connection due to (i) analysts changing jobs, (ii) insiders changing brokers, and (iii) insiders changing jobs. We then create a pseudo-connect dummy for an analyst-firm pair that is connected at a different time through the inside broker link, but not in the period when this dummy is equal to one. We then regress PAFE on the pseudo-connect dummy and see whether we get the same result as we get for the actual connect dummy. If we do, then our inside-broker channel may not be the reason behind what we find.

Consider first an analyst who moves to a not-connected brokerage house but continues to cover the same firm as he did for the inside broker. We define a pseudo-connect dummy equal to 1 when such an analyst issues a new forecast after the firm insider's 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 (1) and (2) of Table 3.

What does this help rule out? For example, let's think of the alternative hypothesis outlined before: time-varying information flows attached to school ties between insiders and analysts. If this alternative were true, we should find the pseudo-connect dummy to be just as significantly negative, since switching to a not-connected broker should not affect the school ties between the analyst as an individual and the firm insider as an individual. On the other hand, the pseudo-connect dummy should be insignificant if our inside brokerage connection is driving the result. As we can see, the coefficient on the pseudo-connect dummy is insignificant. The economic magnitude of the pseudo-connect coefficient is also much smaller than that of true connect, so the insignificance is not simply due to smaller sample size.[7]

Our second falsification test considers the case in which the insider switches to a different broker to execute his trades. Specifically, 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 result is reported in columns (3) and (4) of Table 3. The coefficient on the pseudo-connect dummy is close to -0.003 and not significant.

This test rules out another alternative hypothesis: that our connect dummy is proxying for other time-varying connections between the brokerage firm and the analyst, beyond what is captured by the underwriting affiliation dummy. This could be due to the firm having multiple book-runners (we are capturing the lead underwriter in our dummy), or perhaps due to the broker being a market-maker for the firm, or any other such unobserved active affiliation.

But crucially, in that case, the affiliation between the firm and the brokerage house remains, even if one firm insider changes brokers. Hence, the pseudo-connect dummy should

[7]Note that this result suggests that being co-workers in the same organization facilitates the type of information-sharing we focus on, beyond the personal relationship between the analyst and the broker. While it's unlikely that the personal relationship/friendship between the broker and the analyst ceases to operate as soon as the analyst changes jobs, our results suggest that the information-sharing relationship does seem to taper off relatively soon.

be just as strongly negative and significant even after the insider switches to a new broker, if the information advantage of the old broker's analyst had nothing to do with the insider's trades and was just coming from some kind of brokerage affiliation. Our evidence goes against this alternative: the pseudo-connect coefficient is economically and statistically very close to zero. Therefore, active affiliation of any kind is highly unlikely to be an explanation for our story.

We say highly unlikely instead of impossible because of one possibility: if the insider changing his broker always coincides with the insider's firm changing the particular affiliation in question, then the alternative could still be true. However, each firm in our sample has many insiders, and a lot of them change brokers (some of them change brokers because they move to a different city, etc.). So, while it is possible, it is highly implausible that every time an insider changes her broker, the firm will change its market maker or underwriter.

Our last falsification test is based on the insider moving to a new firm but retaining his old broker to execute his trades. We create another pseudo-connect dummy equal to 1 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 original connection breaking. The result is reported in columns (5) and (6). The coefficient on the pseudo-connect dummy in this case is positive and insignificant. This results raises the bar even higher for explanations such as other unobserved brokerage-firm relationships producing our observed effect: for that to happen, the firm not only needs to change its (unobserved) affiliation each time an insider changes his broker, but also needs to change affiliation each time an insider leaves the firm. This is even more implausible.

In summary, all three falsification tests reinforce our interpretation that the channel through which the inside analyst obtains her information advantage is the insider's brokerage relationship.

4.2 Broker-affiliated mutual funds

Our results on analyst forecast accuracy suggest that analysts working in an insider's brokerage firm are able to utilize the privileged information contained in insider trades to improve their earnings forecast on the insider's firm. In this section, we examine a related but distinct hypothesis: whether the same information is also used by mutual funds affiliated with the insider's broker to trade profitably on the insider's firm.

4.2.1 Return predictability using affiliated mutual fund trades

We first focus on broker-affiliated funds' trading after Form 144 trades and compare it to non-affiliated funds' trading on the same stock in the same quarter. If broker-affiliated funds benefit from the broker's unique advantage in gleaning information from the insider's trades in the trading process, we expect these funds' trades to generate abnormal returns. Specifically, when broker-affiliated funds decrease (increase) holdings of an insider's firm more relative to non-affiliated funds, it should generate negative (positive) abnormal returns. We refrain from analyzing the performance of the entire fund, because a trading a few connected stocks profitably need not have a statistically discernable impact on overall performance.

We start in Table 4 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.[8] To illustrate, consider an example similar to that in Section 4.1. Suppose an affiliated mutual fund manager obtains information through the insider's broker that a large insider sale that everyone else infers is bad news is in fact not so (e.g., a first-in-a-regular-sequence trade, as in Section 6). In this case, she would choose not to change her earlier beliefs on the company, at a time when other funds 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 unaffiliated fund trades. We now focus on testing this prediction.

To do so, we examine the profitability of these connected stock trades as follows. First, we measure mutual funds' trading on a stock as its change of quarterly holding on the stock. To take care of time-invariant stock-specific trading differences across funds, we need to measure a fund's abnormal trading in each stock. We define abnormal trading by a fund as the percent 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). We then construct a calendar-time portfolio long in stocks associated

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

with Form 144 trades in which broker-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 broker-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 holding (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.[9]

In Table 4, Panel B we report the monthly abnormal returns to this long-short portfolio. 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 excess return 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 fourth 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. Similar results obtain when we use the Fama and French (2015) five-factor model and the Hou, Xue and Zhang (2016) Q-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 inside broker's fund is more negative than the prevailing consensus, one could argue that these results are also consistent with the view that the market does appreciate the source of higher profitability of inside fund trades, but short-sale frictions prevent participants from trading all profits 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

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

by 2 analysts). Such stocks are unlikely to have binding short-sales constraints.

In Panel C of Table 4, we re-examine the return predictability result using Fama-MacBeth regressions. In column (1), we define a *Sell* dummy equal to 1 when broker-affiliated funds sell the connected stock more aggressively than their non-affiliated peers over the same quarter, and zero otherwise. In column (2), we define *Abnormal_trade* as the difference in abnormal trading between broker-affiliated and non-affiliated funds. We control for the usual cross-sectional return predictors including size, book-to-market, 1-month return reversal and 12-month momentum. The coefficient on *Sell* is negative and significant, with a magnitude of -0.0038. It indicates that when broker-affiliated funds decrease holding on the stock relative to non-affiliated funds, the stock experiences 38 bps more negative return per month over the next quarter. The magnitude of abnormal returns is similar to what we observed in the calendar-time portfolio strategy. Results in column (2) show similar evidence where the coefficient on *Abnormal_trade* is significantly positive.

Overall, our evidence indicates that (i) broker-affiliated mutual funds sell stocks sold by firm insiders through their brokerage more aggressively, and (ii) following their net trading pattern leads to a profitable trading strategy over the quarter following the insider trade, as the information advantage they enjoy gradually materializes. Overall, these affiliated funds seem to be using their (time-varying) information advantage on stocks connected through the inside broker link to improve trading performance.

4.2.2 Falsification Tests

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. We find evidence that this alternative explanation cannot explain our results. First, recall that we showed in the summary statistics (Table 1, Panel G) that broker-affiliated funds have similar gross and net fund returns as non-affiliated funds. In this section, we conduct several falsification tests to further 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 of these are connected to the fund through the 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 simultaneous *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 5, Panel A reports the results. We see that these portfolio abnormal returns are both magnitude and significance-wise close to zero, regardless of the benchmark model used.[10] So time-varying skills or effort of affiliated versus other fund managers cannot explain our results in Table 4.

In Table 5, Panel B we examine 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.

Our second set of falsification tests considers breaks in the funds-firm connection due to (1) insiders changing brokers and (2) insiders changing jobs, similar in spirit to our falsification tests on analyst forecasts in section 4.1.2. We then examine the trading performance of broker-affiliated funds on stocks that used to be connected through the inside broker link but are not anymore.

Consider first the case where the insider switches to a different broker to execute his trades but stays at the same firm. We create a calendar-time portfolio based on the abnormal trading of broker-affiliated funds relative to non-affiliated funds on the insider's firm following the quarter in which the insider trades through the new broker. These results are reported in Panel A of Table 6. As we can see, the abnormal returns to this long/short portfolio are all close to zero and statistically not significant. The magnitude of abnormal returns is

[10]Given the similarity of results, we do not report results for the Fama-French five-factor or the Q-factor model here, both to save space and, more importantly, to focus on results where we give these placebos the best chance to go against us.

economically negligible, and sometimes it has the wrong sign, compared to what we observe for the truly connected stocks in Table 4.

Our last falsification test is based on the insider moving to a new firm but retaining his old broker for trade execution. We create a calendar-time portfolio based on the abnormal trading of broker-affiliated funds relative to non-affiliated funds on the previously connected stock following a trade by an unconnected insider at the same firm (who does not trade through this fund's brokerage). The results are reported in Panel B of Table 6. The abnormal returns to this long/short portfolio are again economically small and statistically not significant.

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

Finally, one key aspect of the affiliated fund trading profitability results is that they indicate that the market in general does not appreciate the time-varying value of the brokerage affiliation.[11] Given this, one might also expect that the market does not completely figure out that the connected analyst's opinions are relatively more valuable in periods when the insider trades through her brokerage. We find this to be true in the data: one can generate abnormal profits by designing a trading strategy that identifies – ex-ante – the profitability of the connected analyst's recommendations, based on the existence of an insider trade through the analyst's brokerage. Overall, our evidence therefore portrays a consistent story. These results are presented in the Internet Appendix (Tables IA.6 – IA.8) for brevity.

5 Cross-sectional heterogeneity

5.1 Affiliated analysts

Here we examine under what circumstances the inside analyst's information advantage would be most useful. All regressions here are run with sub-sample indicators interacted with the connect dummy in specification (2), and therefore they retain the structure of our baseline tests, including the paired fixed effects. 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

[11]Or even if it does, some friction prevents it from trading all potential profits away.

benchmark the small-firm coefficient to the mean PAFE for analysts forecasting small-firm earnings.

5.1.1 Regulation Fair Disclosure: Before vs. After

After the passage of Regulation Fair Disclosure (henceforth Regulation 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 Regulation FD has effectively curbed the information advantage analysts enjoyed through access to management in the pre-Regulation FD period. It is interesting to examine what happens to the information advantage the connected analysts have from their brokerage-affiliated insider trading after Regulation FD.

One possibility is that Regulation FD curtailed direct channels through which analysts might have had private access to management, but left the inside broker advantage relatively unaffected. This is because with the inside broker channel, the manager is not necessarily deliberately disclosing any material information selectively to the connected analyst. The manager interacts with staff members from the trading desk, and the analyst infers the information through them. This would mean that the inside broker's relative advantage should actually be stronger after Regulation FD.

To test this, we define a time dummy *postFD* equal to 1 for all analyst forecasts issued after the year 2001, and interact it with the connect dummy. These results are reported in Panel A of Table 7. The *connect_postFD* interaction has a coefficient of -0.097 (t=-2.95, a 11.3% reduction relative to the sample mean), while the *connect_preFD* has a coefficient close to 0. This is consistent with our prior that the channel through which our connected analysts become more accurate is not affected by Regulation FD. The insignificant coefficient on the connect dummy before the Regulation FD period is also not surprising, since other non-connected analysts could also have enjoyed access to inside information through direct interactions with firm management before FD.

5.1.2 Which analysts?

Our hypothesis is that analysts employed at the inside broker obtain non-public information on insider trades through their relationship with their colleagues at the brokerage's trading desks. Developing a good relationship takes time. Hence we expect our results to be weaker when the connected analyst has joined the brokerage firm recently and is unlikely to have established a strong relationship with her colleagues who interact with insider-clients. To test this, we create a dummy, *Early2* (*Early3*), indicating whether the analyst is within the first two (three) years of joining this brokerage firm, and interact it with the connect dummy. These results are reported in the first four rows of Table 7, Panel B. Consistent with our hypothesis, the coefficient on the connect dummy is less pronounced and not significant when the analyst has worked at her current firm for less than two or three years. This result supports our hypothesis about the time it takes to develop a relationship with work colleagues in a different division.

The second analyst characteristic we examine is the number of stocks in the connected analyst's coverage portfolio. Clement (1999) argues that analysts have deeper knowledge and insights on a specific firm when they have fewer stocks to cover. This type of expertise might also be crucial for a connected 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, a connected analyst who knows that the firm is considering an acquisition in India might be able to infer its progress. If the analyst did not know this information, such an inference would not be possible. We thus expect that the information our connected analysts gain access to will be more useful when the analyst has fewer stocks to cover. We create a dummy, *One-of-few*, equal to 1 when the number of stocks covered 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 error, while that on the *Connect_one-of-many* (=1-*One-of-few*) dummy is -0.054 (t=-1.66, a 7.3% reduction relative to the sample mean). These results support the hypothesis that being focused helps connected analysts better interpret the information contained in the insider trade.

We also examine whether the effect of being connected on analyst forecast accuracy depends on analysts' skill. On the one hand, skilled analysts may be in a better position to exploit the information advantage through inside brokers since they could combine their unique insights with the additional information and generate more accurate forecasts. On the other hand, our regression specification controls for analyst-firm fixed effects, so we are essentially comparing the forecast accuracy of the connected analyst on the same firm in periods when the insider trades versus when he did not trade. The improvement in forecast accuracy may be small for more skilled analysts because they tend to do well even in periods when insiders did not trade. 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 the same 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 connect and our analyst skill dummy, and report the results in rows 7 and 8 of Table 7, Panel B. As we can see, the coefficient on the connect dummy is significantly larger when the analyst is less skilled, and statistically much stronger. This result indicates that insider information is more useful for connected analysts with lower skill.

Our results rely on the assumption that connected analysts can get access to additional information contained in insider trading beyond what is disclosed in public SEC filings. The information advantage comes from connected analysts' interaction with their trading desk colleague who executes an insider's 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 him, enabling her (the analyst) to exploit the inside broker advantage better. To test this, we create a dummy *Sameloc* 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 connect and the same location dummy. This result is reported in rows 9 and 10 of Table 7, Panel B. The coefficient on the connect dummy is 3.5 times as large when the analyst and insider are from the same MSA, as compared to when they are not located in the same city. This supports our premise that geographic proximity facilitates information flows between the connected analyst and their trading desk colleague who facilitates the insider rade.[12]

[12] 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

Finally, we examine residual analyst coverage, i.e., coverage controlling for size. We find that the absolute 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, when more analysts cover the same stock, there is more competition (Hong and Kacperczyk (2010)). This strengthens incentives for the connected analyst to use all possible information to improve her forecast.

5.1.3 Insider trade and insider's firm characteristics

The first firm characteristic we look at is market capitalization, which has often been used as a proxy for a firm's information environment. Small firms are less likely to be held by institutional investors, and are followed by fewer analysts. Empirically, perhaps as a result of this, information diffusion speed is slower for smaller firms (Hong, Lim, and Stein (2000)). Previous research also documents that outsiders mimicking insider trades are earn more profits in firms with smaller market capitalization (Lakonishok and Lee (2001)). We thus expect that the information obtained through the inside broker connection is more useful among small firms. To test this, we interact the connect dummy with a size dummy indicating whether the firm has above or below median market capitalization, where market capitalization is defined as the firm's market value of equity 12 months prior to the forecast announcement date. These results are reported in the first two rows of Table 7, Panel C. Consistent with our prior, both the magnitude and significance of the connect dummy are 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_bigfirm* is close to zero and not significant at conventional levels.

Again, the private information obtained via insider trading transactions could be more useful to the connected analysts when there is more underlying uncertainty about the firms' future prospects. To test this, we use two variables, monthly return volatility and analyst forecast dispersion, to proxy for information uncertainty about firms' future performance. We again interact the connect dummy with a dummy indicating whether the firm has above

when insiders trade, this possibility is not ruled out or controlled for 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, and their trades help us rule out this possibility.

or below median monthly return volatility or analyst forecast dispersion.[13] Return volatility results are reported in rows 3 and 4, and forecast dispersion results in rows 5 and 6, of Table 7, Panel C. Consistent with our hypotheses, we find that the coefficient on the connect dummy is indeed more pronounced for firms with more volatile stock returns or more dispersed opinions. For example, the coefficient on the connect dummy is -0.15 (t=-3.03, a 13.4% reduction relative to sample mean) when the firm has above median return volatility, while it is only -0.02 (t=-1.01) for less volatile stocks. 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 evidence to be consistent with our hypothesis. The connect dummy is strongly negative in high turnover stocks, with a coefficient of -0.13 (t=-2.86, a 14.5% reduction relative to the sample mean), but it is much smaller in magnitude and not statistically significant in low turnover stocks.

Analyst coverage is a commonly used proxy for firms' information environment. 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 9, Panel C, we regress PAFE on the interaction between connect and another dummy indicating above or below median analyst coverage. Given the strong correlation between analyst coverage and size, we expect the connect dummy to be more pronounced among firms with lower analyst coverage. This is indeed what we find.

We also split the sample based on firms' median book-to-market ratios. Firms with low B/M 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 such stocks. The last firm characteristic we look at is R&D intensity. Firms with high R&D expenditures are inherently difficult to value, given the uncertainty associated with the innovation process, and the expertise required to value it. Analysts who face the challenging task of forecasting earnings of high R&D firms might benefit more from the information obtained through their inside broker connection. Our results are consistent with both these hypotheses.

Next, the information advantage of the connected analysts over other analysts crucially depends on how informative the connected insider trades are for future firm value. The insider trading literature has documented that not all insider trades are equally informative. In the next set of tests, we screen out informative insider trades based on observable trade

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

characteristics, and test whether more informative insider trades lead to more accurate earnings forecasts for connected analysts. First, we examine the total number of trades placed through the one-year period up to the analysts' forecast announcement date. The dummy *Fretrade* (*Infretrade*) is equal to 1 if the total number of insider trades is above (below) the median, and we interact it with the connect dummy. These results are reported in rows 15 and 16 of Table 7, Panel C. The coefficient on the connect dummy is significantly negative only when insiders trade less frequently through this connected brokerage house. The final trade characteristic we look at is the size of the insider trade as a fraction of total shares outstanding. Larger trades are more likely to have information. To test this, we interact the connect dummy with a dummy indicating whether the average trade size for connected insiders is above or below median. The last two rows of the Panel report these results. The coefficient on the connect dummy is two times larger when the average trade size is above the median.

Overall, then, we find that larger and rarer trades give a bigger edge to the inside analyst.

5.2 Affiliated mutual funds

Having established that broker-affiliated funds are able to trade on the privileged information contained in insider trades facilitated by their firm for their own benefit, we examine various firm, fund, and trade characteristics that could amplify the broker-affiliated funds' information advantage. We use the same set of firm and trade characteristics as in our tests on connected analysts' forecast accuracy in section 4.1.1.

The firm characteristics we examine include firm size, book-to-market ratio, idiosyncratic volatility, analyst forecast dispersion, and monthly turnover. Following our conjecture in section 5.1, we expect the information advantage of broker-affiliated funds to be more pronounced among small stocks, stocks with high growth opportunity, more volatile stocks, and stocks with highly dispersed analyst and investor opinions. Each month, we first divide all stocks into two groups based on the median value of a specific stock characteristic. We then construct the same calendar-time portfolio strategy and examine the Carhart (1997) four-factor alpha for each subsample, similar to our baseline results in Section 4.2. The only difference is that we now only require each portfolio to contain at least 15 stocks, and invest in risk-free asset in periods of less than 15 stocks (imposing a stricter criterion of 30 stocks in the portfolio reduces power in our subsamples, without affecting results qualitatively).

The results are reported in Table 8. Consistent with our hypothesis, we find that the abnormal return to broker-affiliated funds' trading is concentrated among stocks where we expect their information advantage will be largest. For example, in rows (1) and (2) when we split the sample based on firm size, the monthly four-factor alpha is 0.85% for small stocks, but only 0.02% for big stocks. Similarly, the abnormal return to broker-affiliated funds' trading is higher for growth stocks, more volatile stocks, and stocks with high forecast dispersion and turnover.

Next we examine trade-level characteristics that could indicate more informative insider trades. First, we measure the total number of trades placed through the insider's brokerage. We split the sample into two based on the median number of insider trades. The abnormal return to broker-affiliated funds' trading is economically larger and more significant when insiders trade less frequently through the connected brokerage house. Bigger trades also lead to higher abnormal returns (rows 15 through 18 in Table 8). Overall, we find that larger and less frequent trades give a bigger edge to the broker-affiliated funds, which is consistent with our results on the connected analysts' forecast accuracy.

Finally, we examine the strength of results across different kinds of fund managers. We split the sample into two based on the number of other managers within the same fund family. Managers who face internal competition from other managers are likely to have a greater incentive to exploit the information advantage from the broker of the insider. Accordingly, we find that abnormal returns to broker-affiliated fund managers are larger when the manager faces internal competition from many other managers. 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 that fund managers who have spent more time in the same fund family show greater economic magnitude of abnormal returns to their trades.

6 The inside broker's information advantage: Channels

We gave an example in the introduction on the nature of the trading instruction – limit orders versus market – being one potential source of the inside broker's information advantage. Clearly, however, this is not the only possible source of such an advantage. Many other channels could also convey similarly valuable information: for example, the broker might know whether the sale of inside stock was accompanied by sales of *other*, unrelated stocks that the insider owns. This additional piece of information, which the broker might possess purely incidentally, and which again the market would not have – could be helpful in inferring whether the trade was more likely to have been information driven or due to liquidity reasons.

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 will be privy to information on whether the insider's family members, for example, his children or wife – who might also have brokerage accounts with him – also traded at the same time and in the same direction as the insider. Yet another possibility is 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 anyone else.

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 – in 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.

6.1 Test of a channel for broker-affiliated funds

In general it is difficult to show definitive evidence of what the broker might know that is informative for the inside analyst but not for the rest of the market after the trade has been disclosed. There could be things that the broker knows but the empiricist never finds out. All we can do is to look for evidence of the following nature: something that eventually becomes clear to everyone including non-connected analysts (we need this for us as econometricians to observe the pattern), that only the inside analyst 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 repeated trading pattern. Suppose the insider starts trading in the same month every year. This 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. In this section, we test this hypothesis.

We identify routine trades following Cohen, Malloy and Pomorski (2012) as insider trades that occur in the same calendar month for three consecutive years. We then define a dummy variable indicating whether a given insider trade is routine or otherwise, which we call opportunistic. Within all routine trades, we further define three dummies to differentiate between routine trades that occur for the first time in the sequence, for the second time in the sequence, and three or more years into the sequence. Using these measures, we examine the quarterly change in broker-affiliated funds' holdings relative to non-affiliated funds' on stocks associated with Form 144 trades.

First, consider an insider trade that constitutes the beginning of a routine sequence. After the insider trades, we should observe that fund managers not affiliated with the inside broker – who have no way to figure out that this trade belongs to a sequence that they will see in the *future*, and therefore think this is an information-driven opportunistic trade – negatively update their prior beliefs about the prospects of the insider's stock, which is likely to be reflected in significant sales of their holdings. Now, if the affiliated manager knows that this is the start of a sequence, he should be much less negative, i.e., not sell as much. Now consider the same insider's trades later in the sequence, i.e., trades in the same month in subsequent years. By this time affiliated and not-affiliated managers would *both* be able to infer that these are likely-to-be-uninformative sequence trades, and they would trade similarly.

These results are reported in Table 9, Panel A. Consistent with our prior, we find that the difference in quarterly trading 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 non-affiliated funds decrease holding 0.025% (t=2.56) more than affiliated 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. Since only the broker-affiliated funds are likely to know that the first trade belongs to a regular trading pattern, their information advantage over non-affiliated funds should be largest at such times. Finally, inside broker-affiliated funds trade more negatively than peers when the trade is indeed opportunistic, suggesting that they are better able to sort out opportunistic trades from potentially repeated ones.

In Panel B, we verify that the direction in which the affiliated funds trade is indeed profitable. First, we show that routine insider trades are *not informative* of declines in future firm value (reminiscent of, and out-of-sample validation for Cohen et al. (2012), who establish this pattern for Form 4 insider trades). Therefore, by not aggressively selling the insider's firm following these trades – including the first-in-sequence trade, as shown in Panel A – affiliated funds avoid unnecessary trading costs. 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 (last row of Panel A).

6.2 Verifying the channel for connected analysts

Here we again use our previously defined dummies differentiating between routine trades that occur for the first time in the sequence, for the second time in the sequence, and three or more years into the sequence. Specifically, we regress (i) an analyst forecast optimism (signed forecast error) measure (column (1) of Table 10), and (ii) our previous forecast accuracy measure (column (2)), on the interaction between these four dummies and the connect dummy.

Looking at the analyst forecast optimism measure, we find that for routine trades, the coefficient on the connect dummy is positive for the first-in-sequence trade. This shows that connected analysts remain significantly more positive than their peers about the future prospects of the insider's firm after observing the first-in-sequence trade. This is consistent with the hypothesis that the connected analyst is the only one who knows that the first-in-sequence insider trade is uninformative. There is no significant difference between their optimism and that of their peers for further-in-sequence trades.

Again, a consistent pattern emerges when we examine forecast accuracy in column (2) using our 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 and significant at the 10% level following the first-year routine trades, it is smaller and becomes insignificant following the second-year routine trades. The coefficient on the connect dummy even becomes positive following the third-year (or beyond) routine trades. The economic magnitude of the connect coefficient on the first-year routine trade is even larger than that of the opportunistic trades, though statistically it is less significant due to the smaller sample size.[14] Like our results on affiliated mutual funds, these results convey a clear message: since only the connected analyst is likely to know that the first trade belongs to a regular trading pattern, their information advantage over non-connected analysts is the largest at such times, and declines thereafter.

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

The results in this section help rule out an important alternative – that of reverse causality. The reverse causality argument here is that at certain points in time, the connected analyst (or fund manager) has a particular information or analysis advantage over everyone else. At these times, she issues better forecasts (or trades in the right direction), and the inside broker, learning from his analyst (or fund manager) colleague, advises the insider to trade in the same direction. In that case, the effect we capture would be spurious.

But our example of the first-in-sequence trade above is one that is *not* particularly informed by anything at the firm; still, the inside analyst and fund manager know something more than the market. There is nothing here that they could have known beyond the fact that this trade will be part of a sequence, and hence, while their compatriots who do not know this might think it is informative, they know it is *not*. In fact, it is this *lack* of informativeness of the trade that is their information advantage. This is not a trading idea that could plausibly have originated from the analyst or the manager.

7 Legality: A discussion

One natural question is whether the effect we document implies some illegal behavior. With regard to the laws surrounding insider trading and related issues, this 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 not be material. Broadly speaking, a piece of information is "material"

[14] 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.

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. Now 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 than is publicly known at that time. Doing so would not be illegal.

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.

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 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 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 – more attention from insider trading law enforcement agencies.

8 Conclusion

Insiders are privy to information about their firms. How does this information get gradually incorporated into prices? Various regulations have been designed and enforced to ensure that this process does not create any unfair advantages for any party involved. As part of such regulations, for example, insiders are required to disclose their precise trades. But does this disclosure make all parties outside the firm equally informed about the motives behind the trade? In this paper, we argue that it does not.

We identify the stock broking house that firm insiders trade through from a form filed with the SEC, and show that analysts and fund managers employed at such 'inside brokers' know better. These connected analysts' forecasts are significantly more accurate, and the connected managers' trades are more profitable than those of their competitors – each of whom can, incidentally, observe the regulatory disclosure of the trade itself. They are also more accurate than their own forecasts or trades in the same stock in any other period when the insider does not trade through the affiliated broker.

Our study has important implications for the role of financial intermediaries in the process of assimilating information into prices. Broking houses, for example, might have an information advantage that they can obtain from their inferences based on the nature of trading instructions from clients – and *clients may not only mean firm insiders.*

Since almost all traders – not just corporate insiders – trade through brokers, the information advantage the broker enjoys in her role as a trading intermediary could be more general. For example, when an activist hedge fund is slowly acquiring shares in a company, the fund's broker would have this information before any filing of 13D forms, which is when such information typically becomes public. Even after the knowledge that an activist hedge fund is acquiring a significant stake in a company becomes public, the broker might still retain an information advantage. For example, through her interactions she may be able to glean information on the level of the hedge fund's commitment – is the fund manager looking to make substantial changes to the company and willing to commit resources to an expensive proxy battle, if needed, or would she likely back down later and be satisfied with token concessions given by the management? Overall, while we focus on insiders in this paper, examining the brokers' information advantage in other contexts might be a fruitful avenue for future research.

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Table 1: Summary Statistics

This table reports the summary statistics for the sample, including number of observations, mean, 25th percentile, median and 75th percentile for all the variables used in the analysis. Panel A reports number of observations, mean, 10th percentile, median and 90th percentile for the variables in Form 144 trades. Multiple trades of the same insider on the same date are treated as one. Variables used in Panels B through F are defined as follows. Percentage absolute forecast error (PAFE) is defined as the absolute value of actual EPS minus analyst forecasted EPS, scaled by stock price and multiplied by 100. Percentage signed forecast error (PFE) 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 1 year after the firm's insiders trade through a brokerage house employing this analyst. Affiliation (affil) 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 house is the lead underwriter for the IPO or SEO. Forecast age (fore_age) is the natural log of the number of days between the forecast announcement and earnings announcement date. The size of insider trades (frac_shrout) is the average number of shares traded by connected insiders as a percentage of total shares outstanding. Number of trades (No_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. Post Regulation FD (postregfd) is a dummy equal to 1 if the forecast is announced after year 2001. Market capitalization (mktcap) is the firm's market value of equity 12 month before the earnings announcement date. Book-to-market ratio (logBM) is the natural log of book value of equity over market value of equity ending in December. Monthly stock volatility (vol) is the rolling standard deviation of the past 36 months' return. Analyst forecast dispersion (disp) 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 (coverage) is the natural log of one plus the number of analysts covering this firm at fiscal year. Stock turnover (turnover) is the monthly trading volume over total shares outstanding averaged over the past six months. Residual analyst coverage (rcoverage) 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 (R&D) is R&D expenses scaled by contemporaneous sales revenue. Number of years working (workyear) is the number of years the analyst has worked at this brokerage house up to the current year. Number of firms covered (numfirm) is the number of firms the analyst followed in a given year. In Panel B, we report the summary statistics for the sample when the connect dummy is equal to 1. In Panel C, we report the summary statistics for the pseudo-connect sample, defined as analyst-firm pairs that are connected at some point but not contemporaneously. Panel D reports the summary statistics for the entire Compustat sample for the same sample period. In Panel E, we report the summary statistics for cumulative abnormal returns around recommendation changes. CAR(0,+1) is the 2-day cumulative abnormal returns following recommendation change. Abnormal return is measured as raw return less either the CRSP value-weighted index return (market adjusted) or the Size-Book-to-market-Momentum matched portfolio return (DGTW adjusted). Recom_age is the log number of days between recommendation announcement day and the most recent earnings announcement day. In Panel F, we report summary statistics for the broker-affiliated mutual funds sample. Broker-affiliated mutual funds are defined as all those mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. Expense 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 years since the current manager took control. Raw monthly return is the fund net return plus expenses.

Panel A: Form 144 trades

	No. of obs.	Mean	p25	Median	p75
Number of insiders per company	11380	18	3	9	21
Number of trades per company	11380	52	5	18	60
Number of insiders per company-year	59462	6	1	3	7
Number of trades per company-year	59462	10	2	5	11
Number of shares traded per trade	591715	149676	3615	10036	34476
Number of shares traded per trade (% of shares outstanding)	591715	0.758%	0.007%	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	0.774%	0.007%	0.026%	0.093%
Number of shares traded per company-year	59462	1489446	25485	109382	393370
Number of shares traded per company-year (% of shares outstanding)	59462	7.538%	0.095%	0.385%	1.234%
Value of shares traded per company-year	59452	30406714	287389	1633965	8461869
Value of shares traded per company-year (% of market cap)	59452	7.717%	0.096%	0.391%	1.269%

Panel B: Full analyst forecast sample

Variables	No. of obs.	Mean	p25	Median	p75
PAFE	582183	1.18	0.05	0.16	0.54
PFE	582183	-0.22	-0.09	0.03	0.21
connect	600686	2.92%	0	0	0
affil	600686	0.64%	0	0	0
fore_age	600686	4.14	3.76	4.50	4.65
frac_shrout	17570	0.20%	0.01%	0.03%	0.08%
No_of_trades	17570	4.50	1.00	2.00	4.00
postregfd	600686	0.65	0.00	1.00	1.00
mktcap	516619	8836.63	457.65	1578.84	5730.99
logBM	496283	-0.93	-1.39	-0.84	-0.37
Vol	579748	11.94%	6.80%	9.93%	14.67%
disp	540076	0.15	0.02	0.04	0.10
turnover	554649	0.90%	0.32%	0.62%	1.13%
coverage	532758	2.39	1.95	2.48	2.94
rcoverage	532757	0.31	0.00	0.33	0.64
R&D	264706	277.68%	0.47%	4.56%	14.72%
workyear	600686	4.31	2.00	3.00	6.00
Numfirm	599995	18	11	15	21

Panel C: Connected forecast sample

Variables	No. of obs.	Mean	p25	Median	p75
PAFE	17240	0.68	0.03	0.11	0.35
PFE	17240	-0.02	-0.03	0.03	0.17
connect	17551	100.00%	1	1	1
affil	17551	2.98%	0	0	0
fore_age	17551	4.09	3.69	4.50	4.63
frac_shrout	17570	0.20%	0.01%	0.03%	0.08%
No_of_trades	17570	4.50	1.00	2.00	4.00
postregfd	17551	0.71	0.00	1.00	1.00
mktcap	16032	12907.83	759.33	2440.61	9081.80
logBM	14900	-1.21	-1.69	-1.11	-0.60
Vol	17122	13.90%	7.35%	11.06%	17.28%
disp	16346	0.12	0.02	0.03	0.07
turnover	16350	1.02%	0.44%	0.75%	1.26%
coverage	16322	2.48	2.08	2.56	3.00
rcoverage	16322	0.26	-0.05	0.28	0.57
R&D	9473	386.64%	0.95%	9.12%	19.05%
workyear	17551	5.03	2.00	4.00	7.00
Numfirm	17539	16	11	16	20

Panel D: Pseudo-connect sample

Variables	No. of obs.	Mean	p25	Median	p75
PAFE	28880	0.72	0.03	0.11	0.35
PFE	28880	-0.05	-0.03	0.03	0.18
connect	29964	0%	0	0	0
affil	29964	2.24%	0	0	0
fore_age	29964	4.09	3.69	4.50	4.63
No_of_trades	29964	0.00	0.00	0.00	0.00
postregfd	29964	0.69	0.00	1.00	1.00
mktcap	27048	13011.54	974.23	3088.22	10039.90
logBM	25982	-0.99	-1.46	-0.93	-0.44
Vol	28789	11.59%	6.81%	9.76%	14.22%
disp	27800	0.13	0.02	0.03	0.08
turnover	27799	0.98%	0.40%	0.72%	1.25%
coverage	27707	2.57	2.20	2.71	3.04
rcoverage	27707	0.27	-0.04	0.29	0.60
R&D	15101	361.86%	0.36%	4.46%	14.89%
workyear	29964	5.07	2.00	4.00	7.00
Numfirm	29930	17	12	16	21

Panel E: Compustat sample

Variables	No. of obs.	Mean	p25	Median	p75
mktcap	43678	2993.95	65.19	271.05	1144.90
logBM	43667	-0.74	-1.25	-0.66	-0.15
Vol	62242	16.17%	8.55%	12.82%	19.32%
Dispersion	36431	0.13	0.01	0.03	0.07
Turnover	62824	0.62%	0.15%	0.37%	0.78%
Coverage	64437	1.29	0.00	1.39	2.08
Rcoverage	64436	0.03	-0.34	0.07	0.44
R&D	37143	379.58%	0.66%	5.17%	17.69%

Panel F: Recommendation sample

	Variables	Measure	No. of obs.	Mean	p25	Median	p75
downgrade	CAR(0,+1)	market adjusted	108599	-1.72%	-3.53%	-1.09%	0.81%
	CAR(0,+1)	DGTW adjusted	108599	-1.53%	-3.38%	-1.04%	0.80%
upgrade	CAR(0,+1)	market adjusted	118830	1.86%	-0.88%	1.16%	3.74%
	CAR(0,+1)	DGTW adjusted	118830	1.62%	-0.87%	1.09%	3.56%

Panel G: Broker-affiliated mutual fund 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	8.0	25.0
Total Net Assets (TNA, millions of USD)	215	387.14	37.21	146.43	410.30
Expense	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
		Affiliated MF	Non-affiliated MF	Diff	
Raw Return Monthly		0.65%	0.64%	0.01%	
Net Return Monthly		0.54%	0.54%	0.00%	

Table 2: Forecast Accuracy of the Inside Broker-affiliated Analyst

This table reports results from panel regressions 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 broker-firm and firm-year fixed effects. In column (3), we control for firm-year and analyst-broker-firm fixed effects. In column (4), we control for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. In column (5), we control for an affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects. All variables are defined as in Table 1. 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)	(2)	(3)	(4)	(5)
connect	-0.1540***	-0.0560***	-0.0667***	-0.0794***	-0.0756***
	(-5.53)	(-2.73)	(-2.68)	(-2.92)	(-2.78)
fore_age					0.0506***
					(6.00)
affil					-0.1622
					(-1.43)
firm FE	yes	no	no	no	no
broker FE	yes	no	no	no	no
year FE	yes	no	no	no	no
broker-firm FE	no	yes	no	no	no
firm-year FE	no	yes	yes	yes	yes
analyst-broker-firm FE	no	no	yes	yes	yes
analyst-broker-year FE	no	no	no	yes	yes
Adj. R-sq	0.344	0.904	0.916	0.929	0.929
No. of Obs.	499459	438393	383659	370578	370578

Table 3: Falsification Tests

This table reports results from three falsification tests. In columns (1) and (2), we consider analysts who change jobs but still cover the same firm. Specifically, we create a pseudo_connect dummy equal to 1 when the analyst issues an earnings forecast within 1 year following a firm insider's trade through the old broker that the analyst no longer works for. In columns (3) and (4), we look at firm insiders who change their brokers but stay at the same firm. Specifically, we create a pseudo_connect dummy equal to 1 when the analyst at the no-longer-connected brokerage issues an earnings forecast within 1 year following the insider's trade through the new broker. In columns (5) and (6), we consider other insiders at the same firm as the connected insider who trade through a different broker. Specifically, we create a pseudo_connect dummy equal to 1 when an analyst issues an earnings forecast on the previously connected firm following a trade by an unconnected insider at the old firm (who does not trade through this analyst's brokerage) within 1 year of the original connection breaking. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

	Analyst changes job but covers the same firm		**Insider changes broker but stays at the same firm**		**Insider changes jobs but keeps her broker**	
	(1)	(2)	(3)	(4)	(5)	(6)
connect		-0.0674**		-0.0673**		-0.0687***
		(-2.56)		(-2.56)		(-2.65)
pesudo_connect	-0.0168	-0.0201	-0.0066	-0.0026	0.0192	0.0234
	(-0.37)	(-0.45)	(-0.22)	(-0.09)	(0.66)	(0.81)
fore_age	0.0509***	0.0506***	0.0509***	0.0506***	0.0510***	0.0508***
	(6.03)	(6.00)	(6.02)	(6.00)	(6.04)	(6.01)
affil	-0.1630	-0.1622	-0.1630	-0.1622	-0.1631	-0.1624
	(-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.	370580	370580	370578	370578	370578	370578

Table 4: Return Predictability: Broker-affiliated Fund Trades in Connected Stocks

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 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. These 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 average excess return, the Fama-French three-factor alpha, the Carhart (1997) four-factor alpha, DGTW-adjusted returns, the Fama and French (2015) five-factor alpha and the Hou, Xue and Zhang (2016) Q-factor alpha for the full sample. Panel C reports the Fama-MacBeth regression results. In column (1), Sell is a dummy equal to 1 when broker-affiliated funds' abnormal change of quarterly holding is less than the non-affiliated funds' abnormal change of quarterly holding on the same stock in the same quarter and zero otherwise. In column (2), "Abnormal_trade" is the difference of abnormal change of quarterly holding between broker-affiliated and non-affiliated funds. Size (LnME) is the natural log of the firm's market capitalization at the end of the June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short-term reversal measure (REV) is the lagged monthly return. The sample period is from 1997 to 2013. We exclude stocks with market capitalization in the bottom quintile of NYSE. ***, **, 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 Holding	-0.03%***	-0.02%***	-0.01%***
	(-13.46)	(-30.93)	(3.62)

Panel B: Calendar-time portfolio strategy: following the affiliated fund's trades

	3-factor alpha	**4-factor alpha**	**DGTW adjusted**	**FF5**	**HXZ**
Long	-0.20%	-0.12%	0.11%	-0.07%	-0.10%
	(-1.13)	(-0.71)	(0.43)	(-0.43)	(-0.53)
Short	-0.71%***	-0.70%***	-0.32%***	-0.56%***	-0.59%***
	(-3.54)	(-3.45)	(-2.59)	(-2.62)	(-2.63)
Long-Short	**0.51%*****	**0.58%*****	**0.43%*****	**0.48%****	**0.49%****
	(2.81)	**(3.19)**	**(3.50)**	**(2.39)**	**(2.47)**

Panel C: Fama-MacBeth regressions

	(1)	(2)
Sell	**-0.0038****	
	(-2.27)	
Abnormal_trade		**1.2784***
		(1.74)
LnME	-0.0001	-0.0002
	(-0.14)	(-0.16)
LnBM	0.0004	0.0005
	(0.17)	(0.25)
Rev	-0.0026	-0.0035
	(-0.20)	(-0.27)
Mom	0.0046	0.0034
	(0.78)	(0.57)
Constant	0.0050	0.0041
	(0.47)	(0.37)
Average R-sq	0.154	0.159
No. of Obs.	20125	20125

Table 5: Falsification Tests: Broker-affiliated Fund Trades

Broker-affiliated mutual funds are defined as all those mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. Panel A 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 B 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' change of quarterly holding is larger than the non-affiliated funds' change of quarterly holding in quarters without Form 144 trades. The strategy goes short in the connected stocks in which the broker-affiliated funds' change of quarterly holding is less than the non-affiliated funds' change of quarterly holding in quarters without Form 144 trades. 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. These portfolios are equally weighted and are held for 3 months following the change of quarterly holding. 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 Fama-French (1993) three-factor alpha, the Carhart (1997) four-factor alpha and the DGTW-adjusted returns for the full sample. The sample period is from 1997 to 2013. We exclude stocks with market capitalization in the bottom quintile of NYSE. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Return predictability: Affiliated fund trades in not-connected stocks at the same time

	3 factor alpha	4 factor alpha	DGTW adjusted
Long	0.02%	0.00%	-0.02%
	(0.47)	(-0.02)	(-0.53)
Short	0.08%**	0.08%**	0.01%
	(2.29)	(2.10)	(0.57)
Long-Short	**-0.06%**	**-0.08%**	**-0.03%**
	(-0.91)	**(-1.17)**	**(-0.65)**

Panel B: Return predictability: Affiliated fund trades in connected stocks in periods without any inside-broker connection

	3-factor alpha	4-factor alpha	DGTW adjusted
Long	0.10%	0.08%	0.07%
	(0.60)	(0.51)	(0.56)
Short	0.14%	0.13%	0.03%
	(0.86)	(0.80)	(0.22)
Long-Short	**-0.04%**	**-0.05%**	**0.04%**
	(-0.26)	**(-0.29)**	**(0.25)**

Table 6: Falsification Tests: Breaks in the Broker-affiliated Fund's Advantage

This table reports return predictability results based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds on pseudo-connected stocks. Broker-affiliated mutual funds are defined as all those mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. Panel A reports the returns and alphas to a calendar-time long/short strategy based on the abnormal trading of broker-affiliated funds relative to non-affiliated funds on the insider's firm following the insider's trading through the new broker. Panel B reports the returns and alphas to a calendar-time long/short strategy based on the abnormal trading of broker-affiliated funds relative to non-affiliated funds on the previously connected firm following a trade by an unconnected insider at the same firm (who does not trade through this fund's brokerage). 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. These portfolios are equally weighted and are held for 3 months following the change of quarterly holding. 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 Fama-French (1993) three-factor alpha, the Carhart (1997) four-factor alpha and the DGTW-adjusted returns for the full sample. The sample period is from 1997 to 2013. We exclude stocks whose market capitalization is in the bottom quintile of NYSE market capitalization.

Panel A: Insider changes her broker but stays at the same firm

	3-factor alpha	**4-factor alpha**	**DGTW adjusted**
Long	-0.34%	-0.25%	-0.26%
	(-1.15)	(-0.85)	(-0.97)
Short	-0.23%	-0.08%	-0.33%
	(-0.74)	(-0.27)	(-1.08)
Long-Short	**-0.11%**	**-0.17%**	**0.07%**
	(-0.38)	**(-0.57)**	**(0.18)**

Panel B: Insider changes her job but keeps the same broker

	3-factor alpha	**4-factor alpha**	**DGTW adjusted**
Long	-0.58%**	-0.55%**	-0.18%
	(-2.25)	(-2.10)	(-0.81)
Short	-0.50%*	-0.42%	-0.39%*
	(-1.66)	(-1.39)	(-1.83)
Long-Short	**-0.08%**	**-0.13%**	**0.21%**
	(-0.31)	**(-0.48)**	**(0.94)**

Table 7: Cross-sectional Tests: Broker-affiliated Analysts

Panel A of this table reports results of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy in different time periods. Connect_preFD (connect_postFD) is the interaction of the connect dummy with a dummy indicating the pre (post) Regulation Fair Disclosure period.

Panel B reports results of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy interacted with various firm and insider trade characteristics, an affiliation dummy and forecast age, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. In the first 2 rows, connect_smallfirm (connect_bigfirm) is the interaction of the connect dummy with a dummy indicating below (above) median market capitalization. In rows 3 and 4, connect_highvol (connect_lowvol) is the interaction of the connect dummy with a dummy indicating above (below) median monthly stock return volatility. In rows 5 and 6, connect_highdisp (connect_lowdisp) is the interaction of the connect dummy with a dummy indicating above (below) median analyst forecast dispersion. In rows 7 and 8, connect_highturn (connect_lowturn) is the interaction of the connect dummy with a dummy indicating above (below) median monthly turnover. In rows 9 and 10, connect_highcov (connect_lowcov) 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 above (below) median B/M ratio. In rows 13 and 14, connect_highrd (connect_lowrd) is the interaction of the connect dummy with a dummy indicating above (below) median R&D intensity. In rows 15 and 16, connect_infretrade (connect_fretrade) 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 is less (more) than 5. In the last 2 rows, connect_smalltrade (connect_bigtrade) is the interaction of the connect dummy with a dummy indicating below (above) median average trade size.

Panel C reports results of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy interacted with various analyst characteristics, an affiliation dummy and forecast age, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. In rows 1 and 2, connect_early2 (connect_late2) 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_early3 (connect_late3) 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. 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 this year is above (below) median. In rows 7 and 8, connect_highskill (connect_lowskill) 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_sameloc (connect_nsameloc) is the interaction of the connect dummy with a dummy indicating that the analyst and insider are located in the same MSA. In rows 11 and 12, connect_highrcov (connect_lowrcov) is the interaction of the connect dummy with a dummy indicating above (below) median residual analyst coverage.

All variables are defined as in Table 1. 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.

Panel A: Before and after Regulation Fair Disclosure

	(1)
connect_preFD	0.0056
	(0.23)
connect_postFD	-0.0968***
	(-2.95)

Panel B: Which inside analysts are more accurate?

	(1)
connect_early2	-0.0422
	(-0.99)
connect_later2	-0.0824***
	(-2.83)
connect_early3	-0.0404
	(-1.17)
connect_later3	-0.0901***
	(-2.79)
connect_one-of-many	-0.0543*
	(-1.66)
connect_one-of-few	-0.1051***
	(-2.99)
connect_highskill	-0.0417
	(-1.42)
connect_lowskill	-0.0982***
	(-2.81)
connect_sameloc	-0.1851***
	(-2.69)
connect_nsameloc	-0.0529**
	(-2.04)
connect_highrcov	-0.1320**
	(-2.05)
connect_lowrcov	-0.0585**
	(-2.25)

Panel C: Insider trade and insider's firm characteristics and connected forecast accuracy

	(1)
connect_smallfirm	-0.1708***
	(-3.49)
connect_bigfirm	-0.0014
	(-0.06)
connect_highvol	-0.1529***
	(-3.03)
connect_lowvol	-0.0225
	(-1.01)
connect_highdisp	-0.1121***
	(-3.06)
connect_lowdisp	-0.0286
	(-0.91)
connect_highturn	-0.1269***
	(-2.86)
connect_lowturn	-0.0085
	(-0.42)
connect_highcov	-0.0413
	(-1.18)
connect_lowcov	-0.1167***
	(-3.28)
connect_growth	-0.0955**
	(-2.32)
connect_value	-0.0404
	(-1.38)
connect_highrd	-0.1718***
	(-2.60)
connect_lowrd	0.0664***
	(-2.35)
connect_infretrade	-0.0795***
	(-2.80)
connect_fretrade	-0.0508
	(-1.05)
connect_smalltrade	-0.0454
	(-1.63)
connect_bigtrade	-0.1166***
	(-2.98)

Table 8: Cross-sectional Tests: Broker-affiliated Mutual Funds

This table reports Carhart (1997) alphas to a long/short portfolio based on change of holdings of broker-affiliated mutual funds relative to non-affiliated funds, in stocks with Form 144 trades for different subsamples. Subsamples are based on firm size, Book-to-market ratio, R&D expenses ratio, idiosyncratic volatility, analyst forecast dispersion, stock turnover, residual analyst coverage, number of insider trades, average trade size, number of competing funds in a family, manager tenure and fund past 12-month performance. All variables are defined as in Table 1. Broker-affiliated mutual funds are defined as all those mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. The strategy goes long in the stocks 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 on the same stock in the same quarter. The strategy goes short in the stocks 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 on the same stock in the same quarter. 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. These portfolios are equally weighted and are held for 3 months following the change of quarterly holding. We require each portfolio to contain at least 15 stocks and invest in risk-free assets in periods of less than 15 stocks. We exclude stocks whose market capitalization is in the bottom quintile of NYSE market capitalization. The sample period is from 1997 to 2013. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Subsamples	Carhart 4-factor alpha	t-stat
Small	0.85%***	2.72
Big	0.02%	0.08
Growth	0.71%***	2.76
Value	0.42%*	1.67
High R&D	0.70%***	2.09
Low R&D	0.22%	1.12
High IVOL	0.83%***	2.88
Low IVOL	0.36%	1.09
High disp	0.78%***	2.78
Low disp	0.30%	1.27
High turnover	0.66%**	2.16
Low turnover	0.19%	0.98
High residual coverage	0.56%*	1.68
Low residual coverage	0.56%**	2.31
Infrequent trades	0.69%***	2.98
Frequent trades	0.18%	0.64
Big trades	0.63%**	2.44
Small trades	0.36%	1.24
Large number of competing funds within broker firm	0.67%**	2.56
Small number of competing funds within broker firm	0.17%	0.52
Managers with longer tenure	0.76%***	3.39
Managers with shorter tenure	0.34%**	2.09
Funds with good past 12-month performance	0.51%*	1.84
Funds with bad past 12-month performance	0.61%***	2.83

Table 9: Affiliated Fund Trading around Routine/Opportunistic Insider Trades

Panel A reports the quarterly change of broker-affiliated mutual funds' holding relative to non-affiliated funds in stocks associated with routine or non-routine Form 144 trades. Broker-affiliated mutual funds are defined as all those mutual funds belonging to a fund family that is part of a financial conglomerate involving a brokerage house. Control funds are those not affiliated with any brokerage houses. Following Cohen et al. (2012), routine trades are those that occurred in the same calendar month for three consecutive years. 1st_in_sequence trade indicates a first-year routine trade. 2nd_in_sequence trade indicates a second-year routine trade. Later_in_sequence indicates a routine trade in the third year or beyond. Non-routine trades indicate opportunistic trades. In Panel B, we construct calendar-time portfolio on stocks with routine/opportunistic insider trades separately. Reported is the Carhart (1997) four-factor alpha of the equal-weighted portfolio. The sample period is from 1997 to 2013. ***, **, and * stand for significance levels of 1%, 5%, and 10%, respectively.

Panel A: Affiliated vs. other mutual fund trading around routine/opportunistic insider trades

	Affiliated	Control	Affiliated - Control
1st_in_sequence trades			
Change in Fund Holding	-0.021%***	-0.046%***	**0.025%****
	(-4.71)	(-9.95)	**(2.56)**
2nd_in_sequence trades			
Change in Fund Holding	-0.015%***	-0.022%***	**0.007%**
	(-2.52)	(-11.52)	**(0.76)**
Later_in_sequence trades			
Change in Fund Holding	-0.020%***	-0.021%***	**0.001%**
	(-4.06)	(-11.06)	**(0.23)**
Non-routine trades			
Change in Fund Holding	-0.035%***	-0.026%***	**-0.009%*****
	(-12.34)	(-28.39)	**(-3.11)**

Panel B: Calendar-time portfolio alphas based on routine/opportunistic trades

	Carhart 4-factor alphas on Form 144 stocks – others
1st_in_sequence trades	0.48%
	(1.32)
2nd_in_sequence trades	0.18%
	(0.62)
Later_in_sequence trades	0.05%
	(0.17)
Non-routine trades	-0.53%***
	(-4.66)

Table 10: Inside Analyst Forecasts around Routine/Opportunistic Trades

This table reports results of the panel regression of signed percentage analyst forecast error (PFE) and absolute forecast error (PAFE) on the connect dummy interacted with four dummies indicating routine or opportunistic insider trades. Forecast error is defined as forecast EPS minus actual EPS. Following Cohen et al. (2012), routine trades are those that occurred in the same calendar month for three consecutive years. Connect_1st_in_seq is the interaction of the connect dummy with a dummy indicating a first-year routine trade. Connect_2nd_in_seq is the interaction of the connect dummy with a dummy indicating a second-year routine trade. Connect_later_in_seq is the interaction of the connect dummy with a dummy indicating a routine trade in the third year or beyond. Connect_nonroutine is the interaction of the connect dummy with a dummy indicating opportunistic trades. All other variables are defined as in Table 1. The sample includes 600,686 earnings forecasts from 1997 to 2013. We control for forecast age, an affiliation dummy, and analyst-broker-firm, analyst-broker-year and firm-year fixed effects in the regression. 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.

	Direction	Accuracy
connect_1st_in_seq	**0.1358****	**-0.1044***
	(2.09)	**(-1.67)**
connect_2nd_in_seq	-0.0331	-0.0585
	(-1.60)	(-0.86)
connect_later_in seq	-0.0090	0.0201
	(-0.33)	(0.37)
connect_nonroutine	-0.0053	-0.0692***
	(-0.26)	(-2.59)
fore_age	-0.0658***	0.0507***
	(-7.50)	(6.00)
affil	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

Inside Brokers: Internet Appendix

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1 Rule 144 and Form 144

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 issue small numbers of shares without registration directly to somebody 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 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. For the vast majority of restricted stock sales, an 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.

An example of Form 144 obtained from SEC's Edgar website is presented as Figure IA.1.

2 Return Predictability of Form 144 Trades

Since we use Form 144 trades, which have not been thoroughly studied in the literature, we conduct a test on the predictability of returns following these trades. We find that Form 144 trades – which are all insider sales – are followed by significant negative returns. In Panel A of Table IA.1, 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 alpha. In Panel B, we run Fama-MacBeth regressions of next month returns on 3 different measures of Form 144 trades, controlling for other common cross-sectional stock return predictors. Results are consistent. This suggests that Form 144 trades are indeed informative for future firm prospects.

3 Robustness Checks

In this section, we conduct more robustness tests on our baseline regression results on analyst forecasts presented in Table 2 in the paper. We report these results in Table IA.2. 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 column (5), when defining the connect dummy, we do not require the insider trading date to be prior to the analyst forecast announcement date. The reason we do this is that a connected analyst may not revise her earnings forecast when the information she obtains from insider trades is consistent with her forecast issued before the insider trading date. In this case, the connected analysts' forecast should still be more accurate than the non-connected ones'. As we can see, the coefficient on the connect dummy is still significantly negative. In the last robustness test, we add two more control variables: forecast frequency and firm-specific relative 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 relative experience (fexp_relative) 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 (6) shows, our result does not change with these two additional controls.

In Table IA.3, we present results from a different type of robustness analysis. Here we use a fixed sample and redo our main results, showing that nothing changes substantially.

4 Forecast accuracy versus optimism

One problem with interpreting the superior 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 of equation (2) and 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 connected analysts become more accurate simply because they are less optimistic, we expect the coefficient on the connect dummy to be significantly positive. Table IA.4 reports these regression results. 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]

5 Target Price Forecast Accuracy

Most sell-side analysts include three quantitative elements in their research reports: earnings forecasts, stock recommendations, and target price forecasts. Our analysis of insider analysts' information advantage has so far focused on earnings forecast and stock recommendations mainly for two reasons. First, the consensus in the analyst forecast literature is that analysts have persistent differential ability in terms of forecasting earnings and making stock recommendations (Loh and Stulz (2009)), while they have at best limited ability to

[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.

persistently provide accurate target price forecasts (Bradshaw, Brown and Huang (2013)). Second, the information advantage that inside analysts might have is more likely to be firm-specific news that could be directly mapped to earnings, but how and when stock price will incorporate that earnings news depends on many other factors such as future market price and valuation level at the end of the forecasting horizon. Nevertheless, we are still interested in understanding whether the information advantage enjoyed by inside analysts extends to their ability to make more accurate stock price forecasts. Specifically, we use the same econometric specification as our baseline regression but replace the dependent variable with the absolute forecast error on 12-month-ahead target price. The absolute forecast error on the 12-month-ahead target price is defined as $\frac{|P12-TP|}{P}$, where P12 is the stock price 12 months following the target price release date, TP is the target price and P is the stock price 1 month before the target price release date.

The results are reported in Table IA.5. We control for the same set of paired high-dimensional fixed effects and an affiliation dummy in the regression. We do not control for the forecast age because for target price forecasts, the forecast age is always 12 months. As we can see, the coefficient on the connect dummy is -0.01 and significant at the 1% level. The mean absolute forecast error on target price across our sample of analysts who were connected to a firm at some period but are not connected currently is 49%, so connected analysts on average reduce forecast error on target price by 2% relative to the mean.[2] The result shows that although there is statistical evidence that inside analysts' information advantage extends to more accurate target price forecasts, economically it is much weaker than their advantage in forecasting firm earnings. This is consistent with our prior that the nature of the private information that inside analysts have access to is related to earnings rather than to stock prices directly.

5.1 Does the market understand the connected analyst's information advantage?

Our results in the previous section indicate that the market in general does not appreciate the time-varying value of the brokerage affiliation.[3] To be consistent with our overall evidence, then, we should also find that the market does not completely figure out that connected

[2]For comparison, Bradshaw, Brown and Huang (2013) document that the average absolute 12-month-ahead target price forecast error is 45% from 2000 to 2009.

[3]Or even if it does, some friction prevents it from trading all potential profits away.

analysts' opinions are relatively more valuable in periods when the insider trades through her brokerage.

5.1.1 Market reactions to connected analysts' recommendation changes

A large literature in finance and accounting documents that the stock market reacts strongly when analysts revise their earnings forecasts or change their recommendations (Stickel (1991), Womack (1996), Barber et al. (2001), Jegadeesh et al. (2004)). Given that connected analysts are more accurate, one question that naturally arises is whether the market pays more attention to their recommendations. If it did, then we would expect prices to react more strongly to recommendation changes by connected analysts in periods when they are better informed due to the insider having traded through their brokerage.

To test this, we examine cumulative abnormal returns around analyst recommendation change dates. We take the market reaction to recommendation changes by connected analysts, relative to other non-connected analysts who forecast at the same time (quarter), to design this test. However, stopping here is not enough. Even if there is a difference in the market reactions, this could arise due to the connected analyst being better than the others on average, and it may not reflect the market understanding that the connected analyst is differentially informed *only at specific and predictable times* – after an insider has traded through the analyst's brokerage. To take care of this, we construct a pseudo-connect abnormal return measure, which is the difference in the market reaction to the connected analyst relative to that for other analysts, but measured *in periods without an affiliated-broker-facilitated insider trading link*. Finally, we examine the difference-in-differences of the market reaction (the difference between abnormal returns to connected and not-connected recommendation changes in periods when the insider traded through her brokerage, minus this same quantity measured when the insider did not trade). The results are presented in Panel A of Table IA.6 for upgrades and in Panel B for downgrades.

We see that in general the market reacts more to recommendation changes by connected analysts than to those of other analysts, *irrespective of whether the period is after an insider trade or not*. Therefore, the aforementioned difference-in-difference coefficient is not statistically significant.

Another way of testing this hypothesis is by running a panel regression of the three-day cumulative abnormal returns around analyst recommendation change (CAR (-1, +1)) on the connect dummy and controlling for firm-year, analyst-broker-firm, analyst-broker-year fixed effects:

$$CAR_{i,j,t}(-1,+1) = \beta_1 Connect_{i,j,t} + \beta_1 Recom\_age + paired\_HDFE + \epsilon_{i,j,t} \tag{1}$$

We get similar results as above using this specification, which we present in Table IA.7.

Overall, this suggests that the market identifies that inside analysts are on average more informed. This is perhaps not surprising, since connected analysts' recommendations are likely to be more valuable than other analysts' in periods in which the insider trades through her brokerage, and no less valuable in other periods – making her average track record better. This average track record is easy to calculate, and hence the market does react more *on average* when the connected analyst changes her recommendation.

But, crucially, the market *does not* seem to recognize the *source* of the inside analyst's advantage – that this comparative information advantage arises only in periods after the insider trades through her brokerage. In the following sub-section, we design a trading strategy to examine whether this is indeed an oversight. To show that it is, we need to demonstrate that there is money left on the table to be earned following connected analyst's recommendations in periods following insider trades, relative to all other periods.

5.1.2 Predictability of earnings announcement returns

We know from the previous section that the market does not react differently to inside analyst recommendations in periods when the analyst is likely to be more informed. Is this evidence of under-reaction? To investigate, we examine 3-day earnings announcement returns following the recommendation change. We focus on earnings announcement day returns instead of general trading days because returns around earnings announcement have a higher signal-to-noise ratio – if there is inside information, its implication will likely become public when the company announces its earnings. We also separate the recommendations into those more favorable than the consensus view (positive) and those less favorable than the consensus (negative). These results are reported in Table IA.8. For the average connected analyst whose recommendation is more positive than the consensus, the 3-day CAR around the subsequent quarterly earnings announcement is 0.83%. However, the average 3-day CAR around earnings announcements for the same analyst in periods not following insider trades 0.87%. Therefore, there is no difference in this case.

The picture is quite different when we consider whether the connected analyst is more negative than the consensus. A relatively more negative view from a connected analyst is associated with a 0.56% lower return around the next earnings announcement day in periods when she is better informed, compared to similar recommendations from her in periods when she is not informed. This effect is statistically significant (t = -2.10) and holds even if we examine DGTW-adjusted abnormal returns around the earnings announcement. So the market price does not seem to fully reflect the incremental value of the inside analyst's recommendation following an insider trade through her brokerage, particularly when the recommendation is more negative than the consensus. This could reflect the fact that the market does not fully appreciate that the inside analyst's information advantage is concentrated in these periods.

These results are consistent with those on affiliated-mutual-fund-trading-based profits. Again, the information advantage seems strong only on the short leg, when the inside analyst is more negative than the prevailing consensus. Just as in the previous case, one could argue that these results are also consistent with the view that the market does appreciate the source of such higher profitability of inside analyst recommendations, but short-sales frictions prevent it from trading all such profits away. While we cannot completely rule this out, again this seems less likely in light of our results in the previous section (i.e., that the market reacts similarly to recommendation changes of inside analysts in periods following and not following insider trades), and also, again, because our sample firms are typically tilted towards large firms where short sales constraints are less likely to be binding.

6 References

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Figure IA.1

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FORM 144

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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.*

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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
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2. (a) Name of person for whose account the securities are to be sold
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   (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
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SEC 1147 (08-07)

Table IA.1: 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 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 alpha. In Panel B, we run Fama-MacBeth regressions of next month return on 3 different measures of Form 144 trades, controlling for other common cross-sectional stock return predictors. In column (1), Form144 sell is a dummy that equals 1 when the stock is associated with any Form 144 trades and zero otherwise. In column (2), the key predictor is log(1+# of Form144 sells) in the month. In column (3), the predictor is the number of shares sold in Form 144 divided by total shares outstanding. Size (LnME) is the natural log of the firm's market capitalization at the end of the June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short-term reversal measure (REV) is the lagged monthly return. We exclude all stocks whose market capitalization is in the bottom quintile of NYSE market capitalization. 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)	(3)
LnME	-0.0013*	-0.0013*	-0.0013*
	(-1.77)	(-1.76)	(-1.88)
LnBM	0.0009	0.0009	0.0009
	(1.04)	(1.03)	(1.08)
REV	-0.0337***	-0.0337***	-0.0337***
	(-4.81)	(-4.81)	(-4.80)
MOM	0.0000	0.0000	-0.0000
	(0.00)	(0.00)	(-0.00)
Form144 sell	-0.0028**		
	(-2.30)		
log(1+# of form144 sells)		-0.0026**	
		(-2.26)	
# of Form144 shares sold/shrout			-0.1133
			(-0.94)
Constant	0.0169**	0.0168**	0.0170**
	(2.57)	(2.56)	(2.60)
Adj. R-sq	0.032	0.032	0.032
No. of Obs.	1094876	1094876	1094876

Table IA.2: Robustness of Analyst Forecast Tests

This table reports various robustness checks of the baseline regression. 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 forecast error. In column (5), when defining the connect dummy we do not require the insider trading date to be prior to the analyst forecast announcement date. In column (6), we add two additional control variables. Forecast frequency is number of forecasts issued by an analyst for a particular firm during the year ending five days before the current forecast. Fexp_relative 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) Sale could be after forecast	(6) Additional controls
connect	-0.0982**	-0.0435***	-0.2546***	-0.1672***	-0.0577**	-0.0692**
	(-2.44)	(-2.72)	(-2.59)	(-2.71)	(-2.44)	(-2.53)
fore_age	0.0644***	0.0428***	0.1035***	0.0795***	0.0509***	0.0492***
	(4.33)	(8.51)	(4.60)	(5.15)	(6.03)	(4.25)
affil	-0.3298*	-0.0835	-0.8012**	-0.5438**	-0.1619	-0.1619
	(-1.72)	(-1.25)	(-2.19)	(-2.16)	(-1.43)	(-1.41)
forecast frequency						-0.0061
						(-1.34)
fexp_relative						0.0017
						(0.07)
firm-year FE	yes	yes	yes	yes	Yes	yes
analyst-broker-firm FE	yes	yes	yes	yes	Yes	yes
analyst-broker-year FE	yes	yes	yes	yes	Yes	yes
Adj. R-sq	0.943	0.923	0.953	0.950	0.929	0.930
No. of Obs.	370672	370672	381745	382552	370672	364922

Table IA.3: Forecast Accuracy of the Inside Analyst (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 broker-firm and firm-year fixed effects. In column (3), we control for firm-year and analyst-broker-firm fixed effects. In column (4), we control for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. In column (5), we control for an 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)	(2)	(3)	(4)	(5)
connect	-0.1725***	-0.0614***	-0.0603**	-0.0712***	-0.0756***
	(-5.83)	(-2.66)	(-2.56)	(-2.71)	(-2.78)
fore_age					0.0506***
					(6.00)
affil					-0.1622
					(-1.43)
firm FE	yes	no	no	no	no
broker FE	yes	no	no	no	no
year FE	yes	no	no	no	no
broker-firm FE	no	yes	no	no	no
firm-year FE	no	yes	yes	yes	yes
analyst-broker-firm FE	no	no	yes	yes	yes
analyst-broker-year FE	no	no	no	yes	yes
Adj. R-sq	0.330	0.907	0.916	0.929	0.929
No. of Obs.	370578	370578	370578	370578	370578

Table IA.4: Forecast Accuracy vs. Optimism

This table reports the regression results of the signed percentage analyst forecast error (PFE) on the connect dummy, an affiliation dummy and forecast age, controlling for 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)
fore_age	-0.0659***
	(-7.50)
affil	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.5: Target Price Forecast Accuracy of the Insider Analyst

This table reports results of the panel regression of analyst absolute forecast error on target price (TPERROR) on the connect dummy. The dependent variable is |P12-TP|/P, P12 is the stock price 12 months following the target price release date, TP is the target price and P is the stock price 1 month before the target price release date. The dependent variable is winsorized at the 1% and 99% levels. We control for an affiliation dummy and analyst-broker-firm, analyst-broker-year and firm-year fixed effects. The sample includes 1,239,715 target price forecasts from 1999 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	-0.0119***
	(-2.83)
affil	-0.0200
	(-1.45)
analyst-broker-firm FE	yes
analyst-broker-year FE	yes
firm-year FE	yes
Adj. R-sq	0.921
No. of Obs.	1008458

Table IA.6: Market Reaction to Recommendation Changes by the Inside Analyst

This table reports the 3-day cumulative abnormal returns around connected and pseudo-connected analysts' recommendation change. We define an analyst's recommendation as connected if the recommendation is issued by an analyst who is employed by a brokerage through which firm insiders trade and the announcement date is within 1 year following the insider trade date. Pseudo-connection is defined as recommendations issued by an analyst who was connected with the firm at some point in time but is not connected in the current period. The control sample is the never-connected analysts who cover the same firm as the connected (or pseudo-connected) analysts in the same quarter. In the right-most column, we report the difference in CAR (-1, +1) between the connected and pseudo-connected analysts' recommendation change with respect to their control sample. Abnormal return is measured as raw return less the return on either the market (market-adjusted) or Size-Book-to-market-Momentum matched (DGTW-adjusted) portfolio. In Panel A, we report the results for upgrade recommendation changes, and in Panel B, we report the results for downgrade recommendation changes. Recommendation initiations are excluded from this sample. The sample period is from 1997 to 2013.

Panel A: Upgrades

	Connect	Control	Connect minus control	Pseudo-connect	Control	Pseudo- connect minus control	Diff-in-Diff
Market-adjusted CAR(-1,+1)	3.19%***	2.33%***	0.86%***	2.89%***	2.40%***	0.49%**	0.37%
	(13.51)	(10.57)	(3.23)	(13.92)	(14.00)	(2.03)	(1.03)
DGTW-adjusted CAR(-1,+1)	2.95%***	2.23%***	0.72%***	2.67%***	2.02%***	0.65%***	0.06%
	(13.16)	(10.56)	(2.88)	(13.99)	(12.94)	(2.93)	(0.19)

Panel B: Downgrades

	Connect	Control	Connect minus control	Pseudo-connect	Control	Pseudo- connect minus control	Diff-in-Diff
Market-adjusted CAR(-1,+1)	-4.10%***	-2.89%***	-1.21%***	-2.66%***	-2.05%***	-0.61%**	-0.60%
	(-13.64)	(-11.81)	(-4.03)	(-12.12)	(-12.03)	(-2.42)	(-1.52)
DGTW-adjusted CAR(-1,+1)	-3.80%***	-2.70%***	-1.10%***	-2.50%***	-1.82%***	-0.68%***	-0.41%
	(-13.32)	(-11.74)	(-3.82)	(-11.85)	(-11.26)	(-2.8)	(-1.10)

Table IA.7: Market Reaction to Recommendation Changes of the Inside Analyst

This table reports results of a regression of cumulative abnormal returns following recommendation change on the connect dummy, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effects. The dependent variable is the 3-day cumulative abnormal returns CAR (-1,+1) around the recommendation change. Abnormal return is measured as raw return less the return on either the market (market-adjusted) or Size-Book-to-market-Momentum matched (DGTW-adjusted) portfolio. All variable definitions appear in Table 2. Recommendation initiations are excluded from the sample. 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.

	Market-adjusted		DGTW-adjusted	
	CAR (-1 ,+1)	CAR (-1 ,+1)	CAR (-1 ,+1)	CAR (-1 ,+1)
	upgrade	downgrade	upgrade	downgrade
connect	-0.0111	-0.0242	-0.0129	-0.0169
	(-0.77)	(-1.31)	(-0.86)	(-1.00)
analyst-broker-firm FE	yes	yes	yes	yes
analyst-broker-year FE	yes	yes	yes	yes
firm-year FE	yes	yes	yes	yes
Adj. R-sq	0.555	0.559	0.547	0.558
No. of Obs.	6926	8455	6926	8455

Table IA.8: Predictability of Earnings Announcement Returns

This table reports the 3-day cumulative abnormal returns of the first quarterly earnings announcement following connected and pseudo-connected analysts' recommendation change. We define an analyst's recommendation as connected if the recommendation is issued by an analyst who is employed by a brokerage through which firm insiders trade and the announcement date is within 1 year following the insider trade date. Pseudo-connection is defined as recommendations issued by analysts who were connected with the firm at some point in time but are not connected in the current period. In the right-most column, we report the difference in CAR (-1,+1) between the connected and pseudo-connected analysts' recommendations. Abnormal return is measured as raw return less the return on either the market (market-adjusted) or Size-Book-to-market-Momentum matched (DGTW-adjusted) portfolio. In Panel A, we report the results for recommendations that are above the prevailing consensus recommendation, and in Panel B, we report the results for recommendations that are below the prevailing consensus. Recommendation initiations are excluded from this sample. The sample period is from 1997 to 2013.

Panel A: Recommendation > consensus

	Connect	Pseudo-connect	Connect-pseudo
Market-adjusted CAR(-1,+1)	0.83%***	0.87%***	-0.04%
	(4.03)	(4.29)	(-0.13)
DGTW-adjusted CAR(-1,+1)	0.65%***	0.74%***	-0.09%
	(3.31)	(3.90)	(-0.34)

Panel B: Recommendation < consensus

	Connect	Pseudo-connect	Connect-pseudo
Market-adjusted CAR(-1,+1)	0.16%	0.72%***	-0.56%**
	(0.82)	(3.87)	(-2.10)
DGTW-adjusted CAR(-1,+1)	0.03%	0.56%***	-0.52%**
	(0.19)	(3.18)	(-2.07)