Inside Brokers

Frank Weikai Li   Abhiroop Mukherjee   Rik Sen*

May 2017

ABSTRACT

We identify the stock broking house that firm insiders trade through, and show that analysts employed at such "inside brokers" have a distinct information advantage over other analysts, *even after* the trade is publicly disclosed. Our results challenge the common perception that information asymmetry arising from insider trading is only acute before trade disclosure. Unlike many other sources of analyst comparative advantage, the effect we document is stronger after Regulation Fair Disclosure, and hence, still very topical. We show that one source of the broker's superior information is his knowledge of the nature of a trading instruction, which facilitates inference about the trade's information content. Overall, our evidence has important implications for regulations needed to address information asymmetry arising from the process of trading, which brokers in particular are in a unique position to exploit.

JEL: G24, G30, G34, G38

Keywords: Insiders, Brokers, Analysts, Information Transmission

* Li and Mukherjee are at HKUST; Sen is at the University of New South Wales. We are grateful to Vikas Agarwal, Sumit Agarwal, Nicholas Barberis, Utpal Bhattacharya, Justin Birru, Kalok Chan, Vidhi Chhaochharia, Darwin Choi, Lauren Cohen, Henrik Cronqvist, Sudipto Dasgupta, Allaudeen Hameed, Harrison Hong, Marcin Kacperczyk, Alok Kumar, George Korniotis, Sun Lei, Dong Lou, Gustavo Manso, Ron Masulis, Kasper Nielsen, Wenlan Qian, David Reeb, Tao Shu, Laura Starks, Sheridan Titman, Baolian Wang, John Wei, David Yermack, and in particular our discussants Yawen Jiao, Roger Loh, and Tong Yao, as well as seminar audiences at the ABFER, CUHK Shenzhen, the EFA, Chinese University of Hong Kong, HKUST, Humboldt University, Indian School of Business, LMU, NTU, University of Lancaster, University of Miami, University of New South Wales, and the University of Sydney for useful comments. We also gratefully acknowledge financial support from the General Research Fund of the Research Grants Council of Hong Kong (Project Number: 692313). Li also thanks Princeton University for hosting him for a part of the time during which this research was conducted.

Inside Brokers

ABSTRACT

We identify the stock broking house that firm insiders trade through, and show that analysts employed at such "inside brokers" have a distinct information advantage over other analysts, *even after* the trade is publicly disclosed. Our results challenge the common perception that information asymmetry arising from insider trading is only acute before trade disclosure. Unlike many other sources of analyst comparative advantage, the effect we document is stronger after Regulation Fair Disclosure, and hence, still very topical. We show that one source of the broker's superior information is his knowledge of the nature of a trading instruction, which facilitates inference about the trade's information content. Overall, our evidence has important implications for regulations needed to address information asymmetry arising from the process of trading, which brokers in particular are in a unique position to exploit.

JEL: G24, G30, G34, G38

Keywords: Insiders, Brokers, Analysts, Information Transmission

1. Introduction

Insiders, by definition, have favored access to private information about their firm; and a large literature shows that they are able to trade on this information to their own benefit[1]. But if such insider trades become a substantial part of stock turnover, other uninformed traders face the risk of being adversely selected against, affecting their ability 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. These laws exist in almost all countries by now, and such laws and the agencies charged with their enforcement focus closely on anyone involved professionally with any firm; and hence, in a position to glean private information – like lawyers, accountants etc.

Surprisingly, however, the law and its enforcement agencies mostly ignore people professionally involved with firm insiders, whose job makes them just as likely to glean private information through their interaction with the insider. In this paper we look at one such group – the stock broker through whom the firm insider trades.

We show that during the trading process, some of the inside information advantage – *beyond that contained in the public disclosure of the trade itself* – passes to the broker used by the insider. One *sufficient condition* is to show evidence of the equity analyst who covers the insider's firm at the same brokerage benefiting from this and making more accurate earnings forecasts. In terms of economic magnitude, we find that an analyst covering a firm issues 10-20% more accurate forecasts of annual earnings after the insider has traded through her brokerage, relative to 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. The inside broker's information advantage, therefore, is substantial.

Perhaps just as importantly, our results also imply that this information advantage is relatively *long-lived* –since these analyst forecasts are mostly issued *after the occurrence of the trade itself becomes public knowledge* through SEC filings, our evidence suggests that not all of the inside broker's information advantage is dissipated by the trade disclosure. So, although the law requires that insiders reveal trades in their companies – in particular the number of shares traded and the trade date – publicly and within a short time window, this disclosure is *not* sufficient in eliminating all obvious sources of information

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

asymmetry arising from the insider trading process. This is an important finding, because the current regulatory regime, as well as most of the academic literature on this topic operates under that assumption, so our evidence makes a case for modifying it.

The plausibility of our narrative depends on the premise that equity analysts are very likely to follow publicly disclosed trades of insiders at the companies they cover. When an analyst realizes that her own firm acted as broker for a particular trade, given her incentive to generate better research reports, she might communicate with her colleague who interacted with the insider and 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 trade itself is publicly disclosed.[2]

Some sales of company shares by insiders (specifically, sales of restricted and control shares) have to be reported to the SEC on form 144, which require information on the broker used for the transaction. We take advantage of this requirement to identify the broking house covering the insider's firm. In order to identify the causal link of our interest, we exploit the granularity of our panel data structure. The unit of observation in our data is at the analyst-broker-firm-time level – the most updated forecast given by an analyst, working at a particular brokerage, on a particular firm, in a particular year. This allows us to control for unobserved heterogeneity by using a rich set of fixed effects for every pair-wise combination of analyst-broker, firm, and time, i.e., dummy variables for each analyst-broker-firm combination, firm-time combination, and analyst-broker-time combination. We can, therefore, rule out a number of alternative possibilities that could give rise to the empirical pattern we observe.

For example, the firm-time fixed effects control for the forecast accuracy of all analysts covering the firm at the same time, and helps 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 include broker-analyst-firm fixed effects, the identification of our effect comes from earnings forecasts by a specific analyst at the insider's broker showing higher accuracy in the period after the trade, relative to her *own* forecasts in other periods on the same firm. As a result, any omitted variable that is invariant at the broker-analyst-

[2] We list more such sources of the inside broker's information advantage in Section 4.

firm level (for example firm-specific analyst skill) does not affect our inference.[3] Analyst-broker-time fixed effects help control for time-varying analyst or brokerage level unobservables, such as analyst experience, accuracy, or the possibility that in some years the brokerage has less trading business from its clients resulting in it becoming resource constrained, which in turn could lead to worse forecast accuracy of its analysts due to their inability to do adequate research.

In our econometric specification, therefore, we only need to control for links between analyst forecast accuracy and insider trading that vary at the analyst-broker-firm-time level. One such possibility is an investment bank strengthening ties with a firm because of being an underwriter in a securities issuance. Another possibility is that forecasts given closer to the earnings announcement may be more informative. To account for these, we control for underwriting affiliation of the insiders' firm, as well as the difference between the date of the forecast and the earnings announcement date. Moreover, we perform a series of falsification tests to rule out alternative explanations based on time-varying personal relationships or other types of unobserved (to the econometrician) business ties between the insider's firm and the brokerage.

We find that the connected analyst's information advantage is greater for firms whose stocks trade in a worse information environment: smaller firms, firms with higher return volatility, higher market-to-book ratios, those with higher dispersion of analyst forecasts, and those with higher R&D expenses. We also find evidence that the effect is stronger for firms for which competition among analysts is more severe, controlling for firm size. This is consistent with analysts having greater incentives to gather information from all sources especially when they face greater competition. Further, we find that the advantage of a connected analyst is greater following insider trades that are larger and less frequent.

Next, thinking through the chain of information flow, we hypothesize that an analyst who has just joined a brokerage firm may take some time to establish a relationship with the brokers of various insiders that are her firm's clients. Consistent with this, we find that the advantage of the connected analyst shows up strongly only two or three years after she joins a new brokerage firm. Similarly, obtaining information – leading to a stronger effect of insider trades on forecast accuracy – would be

[3] Another example of an analyst-firm level time invariant effect is school ties between a particular analyst and an insider. We know such ties can lead to better forecasts (e.g., Cohen, Frazzini and Malloy, 2010); one might wonder if our results are simply a restatement of these earlier results. Controlling for broker-analyst-firm fixed effects subsumes any such effect of school ties.

easier if the analyst can interact face-to-face with the broker of the insider. This would be easier when they are in the same location. We also find evidence consistent with this hypothesis.

Interestingly, 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.

Another interesting question in our context is whether the market figures out that connected analyst opinions are relatively more valuable. We find that on average, the market does respond more to recommendation changes by connected analysts. This is, perhaps, not surprising for the following reason. Connected analyst recommendations are more valuable than other analysts' in periods in which the insider trades through her brokerage, and no less valuable in other periods, making her "on average" a better analyst. The market can identify this relatively easily from her forecasting/recommendation record, and it does.

But, crucially, the market *does not recognize* the source of this ability to forecast/recommend better – that the higher recommendation value of the connected analyst arises *only* in periods when the insider trades through her brokerage. Hence, one can generate abnormal profits by designing a trading strategy that identifies ex-ante the profitability of connected analyst recommendations, based on the existence of an insider trade through the analyst's brokerage. Such profits are particularly strong on the short leg, when the inside analyst is more negative than the prevailing consensus. Overall, these results are consistent with the view that the market either does not appreciate the source of higher profitability of inside analyst recommendations, or even if it does, some friction prevents it from trading all potential profits away.

Finally, 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 the 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 trade at the same time frame over a few (say, three) consecutive years, all analysts will realize this is a regular sequence and hence not information driven. However, when the January trade happens *for the first time*, they would not be able to infer that this is going to be a regular and therefore uninformative occurrence. But the inside analyst might know this, if the information gets conveyed to the insider's broker. So the inside analyst'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. Of course, the inside analyst also has significant information advantage on the irregular (i.e., not-in-a-sequence, and hence more likely to be informative) trades, as one might expect.

This result on the inside analyst'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 would be that at certain points in time, the connected analyst has particular information or analysis advantage over everyone else. At these times she issues better forecasts, and also recommends the insider to trade. However, our first-in-a-regular-sequence trade is an example of a trade which is not particularly informed about anything at the firm; yet, the inside analyst 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 inside analyst's superior information or analysis, so reverse causality cannot explain our result here.

Our study is related to studies which show that brokers may be able to use the information 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 that of 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. 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, unlike 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 himself, who conducted analysis independently, and recommended the trade to the insider and their other clients. If this were true, even then in the data one would observe – like in this literature – that the inside broker's 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.

Our study also contributes to the literature examining the role of financial analysts in the price formation process. 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 el 2004). As analysts are rewarded based on the accuracy of their earnings forecasts and recommendations (Hong and Kubik 2003), they should have strong incentives to make use of all available information related to future firm performance and abnormal returns. One frequently cited source of analysts' information advantage is their access to private information through their interactions with firm managers (e.g., at visits to company headquarters, investor office meetings, and broker-hosted investor conferences). For example, Malloy (2006) finds that local analysts are more accurate than other analysts, suggesting that geographical proximity facilitates information flows between firm managers and analysts. Cohen, Frazzini and Malloy (2008) document that analysts who have an educational link to company management outperform others on their stock recommendations. Green, Jame, Markov, and Subasi (2014) find that access to management at broker-hosted investor conferences leads to more informative analyst research. All of these studies document selective disclosure from managers as an important source of information advantage for analysts, especially during 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 lasts well beyond Reg FD.

The rest of the paper is organized as follows. Section 2 describes our data, Section 3 presents our empirical results, Section 4 discusses some sources of the inside broker's information advantage, Section 5 contains a discussion on the legal implications of our findings, and Section 6 concludes.

2. Data

We obtain analyst forecast and actual earnings data from I/B/E/S. Insider trading data and information about the broker of the insider is obtained from Form 144 file of 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 the details of the background of the regulations that require the filing of Form 144 and the nature of the information in these forms in the Appendix. Table 1 of the Appendix shows that insider trades reported on Form 144 are, on average, informative about future returns of the firm. We manually standardize the broker names reported by different insiders and hand-match these names to I/B/E/S brokers.[4] Information about investment banks involved in security issuances are obtained from SDC Platinum database. Firm characteristics are obtained from S&P Compustat database.

Our sample starts in 1997, which is the first year for which there is sufficient coverage of Form 144 data in Thomson Financial Insider Trading database, and ends in 2013. After matching 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 are a median of five Form 144 trades, and they aggregate to median of 0.4% of the company's shares outstanding. We present more details on these trades in Table 1. 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 Table 2 we present summary statistics for key variables used in our analysis.

3. Empirical Analysis

In this section, we investigate our main hypothesis, that is, whether the analyst employed by the insider's brokerage firm has an information advantage over other analysts following insider trades. We also examine where in the cross-section of firms, trades or analysts such connections create stronger inside information advantage.

3.1 Connected analysts and forecast accuracy

Our main measure is analysts' scaled annual percentage absolute EPS forecast error (PAFE). The PAFE for stock *j* in fiscal year *t* for analyst *i* 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 is the analyst's forecast.

[4] We use the mapping between the broker identifier and broker name from the 2007 vintage of I/B/E/S, since the latest vintage does not have this information.

$$PAFE_{i,j,t} = 100 * |Actual\ EPS_{j,t} - Forecasted\ EPS_{i,j,t}| \ / \ Price_{j,t-1} \quad (1)$$

We run panel regressions of PAFE on a connect dummy - our key explanatory variable, and control for various high dimensional fixed effects (HDFE), such as at the level of each stock-year, stock-analyst, and analyst-year.

$$PAFE_{i,j,t} = a + b*connect_{i,j,t} + c*affil_{i,j,t} + d*fore\_age_{i,j,t} + \boldsymbol{X}_{i,j,t} + paired\ HDFE + e_{i,j,t} \quad (2)$$

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 0 otherwise. Affil is an indicator for the parent of the brokerage house having an investment banking relationship with the insider's firm, fore_age controls for the vintage of the forecast to make sure that we do distil our effect out from that of forecast recency.

In our baseline regression, we examine whether an analyst issues more accurate earnings forecasts on firms where at least one insider trades through the brokerage employing the analyst within the same 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, we show that our results are also robust to the more orthodox approach with a variety of different control variables.

Table 3 reports the 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). Consistent with our hypothesis, analysts are indeed more accurate at forecasting the firms' earnings when the firms' managers have traded through the brokerage that she works for 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 2, panel C). Hence this represents a 20.8% reduction in average forecast errors. In column (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, analysts-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 forecast on the firms' annual EPS, compared to (i) all other analysts following the same firm in the current fiscal year, (ii) her own forecasts on other non-connected firms at the same time; and (iii) her own forecasts issued on the same firm during other periods when no firm insider traded through her brokerage firm.

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, that are not fully captured 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 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 are on average lower than 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 brokerage houses forecast differently. Our results hence could be driven by this underwriting affiliation rather than through 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 (affil) 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 3 reports the 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 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 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 (1) the magnitude is measured with respect to the analyst's *own* forecast accuracy in periods without the inside information advantage; and (2) 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 leave out cases where there was no differential information transmitted in the trading process.

3.2 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 forecast on the connected firm. Our use of a rich set of paired firm, analyst, broker and time fixed effect 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 could potentially be consistent with our result. For example, Cohen, Frazzini and Malloy (2012) find that analysts who have attended the same college as the firm managers have information advantage on the connected firm when making recommendations. Since the school ties between analyst and insider is always there, if the information flow from insider to analyst is not time-varying, our analyst-firm fixed effect will capture any such effect. However, the information flow from insider to analyst may well be time-varying. Insiders may have significant private information only in some periods, and 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 substantiate the channel that the inside analyst gets more accurate information because insiders trade through their brokerage firm we conduct three falsification tests. Specifically, we consider breaks in the analyst-firm connection due to (1) analysts changing jobs, (2) insiders changing brokers; and (3) insiders changing jobs. We then create a pseudo connect dummy between an analyst and a firm who used to be connected through the inside broker link, but are not anymore. 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.

Consider first an analyst who moves to a non-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 one when such an analyst issues a new forecast following the firm insider's trade 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 4.

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 changing to a non-connected broker shouldn't affect the school tie 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 pseudo connect dummy is -0.02 but insignificant. The economic magnitude on the pseudo connect dummy is also much smaller compared to the true connect dummy, so the insignificance is not simply due to smaller sample size on the pseudo connect dummy.[5]

Our second falsification test considers the case that the insider switches to a different broker to execute his trades. Specifically, we create a pseudo dummy equal to one 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 4. The coefficient on the pseudo connect dummy is close to -0.003 and not significant. This result again rules out a time-varying information flow story, but is consistent with the channel that we propose in this paper.

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 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. This is not the case, the pseudo connect coefficient is economically and statistically

[5] 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 cease relatively soon.

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

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 a pseudo connect dummy equal to one when the analyst issues an earnings forecast on the previously connected firm following a trade by an unconnected insider at the same firm (who does not trade through this analyst's brokerage) within one year of the original connection breaking. The result is reported in columns (5) and (6) of table 4. The coefficient on the pseudo connect dummy in this case is positive and insignificant. Again, this result helps rule out both the alterative explanations listed previously in this section. This leaves an even higher bar for explanations such as unobserved active brokerage-firm relationships: for our results to be explained by any such story, not only does the firm need to change its affiliation each time an insider changes his broker, but also it has to change affiliation each time an insider leaves the firm.

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

3.3 Cross-sectional heterogeneity

Here we examine under what circumstances the inside analyst's information advantage would be most useful. We examine various firm-level, trade-level and analyst-level characteristics that could amplify the connected analysts' information advantage.

3.3.1 Firm characteristics and forecast accuracy of connected analysts

The first firm characteristic we look at is firm size, 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 more profitable among 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. We also control for firm-year, analyst-broker-firm and analyst-broker-year fixed effects in this and all the remaining regressions. The result is reported in column (1) of table 5. Consistent with our prior, both the magnitude and significance of the connect dummy is stronger for small firms (coefficient of -0.17, t=-3.49, a 13.9% reduction relative to sample mean), while the coefficient on connect_bigfirm is close to 0 and not significant at conventional levels.[6] Again, the private information obtained via insider trading transaction could be more useful for 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 or below median monthly return volatility or analyst forecast dispersion.[7] The results are reported in columns (2) and (3) of table 5. Consistent with our hypothesis, we find 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 column (4), 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 sample mean), but 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 column (5), 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

---

[6] In our cross-sectional tests, we discuss all economic magnitudes with reference to the average PAFE *in the relevant sub-sample*, e.g., in this case, we benchmark the coefficient reported to the mean PAFE for analysts forecasting *small firm* earnings, who are connected at some time with the firm but not currently connected.

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

with fewer analyst coverage. This is indeed what we find. In column (6) 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: controlling for 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.

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 assets in place. So we expect inside information to be particularly useful for connected analysts among such stocks. The result is reported in column (7) of table 5. The coefficient of the connect dummy among growth stocks is -0.10 (t=-2.38, an 18.5% reduction relative to sample mean), twice as large as the coefficient among value 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, and expertise required to value innovation. 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. To test this, we interact our connect dummy with a dummy indicating whether the firm has above or below median R&D intensity. This result is reported in the last column of table 5. Consistent with our hypothesis, the economic magnitude on the connect dummy is indeed more pronounced among firms engaging in more R&D activities.

3.3.2 Trade characteristics and forecast accuracy of connected analysts

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 (Cohen, Frazzini and Malloy 2010) find that the 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 other channels through which analysts might have 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 the trading desk, and the analyst infers the information through them. This would mean that the inside broker 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. The result is reported in column (1) of table 6. The connect_postFD interaction has a coefficient of -0.097 (t=-2.95, a 11.3% reduction relative to 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 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.

Further, 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 examine screen out informative insider trades based on observable trades 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 analysts' forecast announcement date. The dummy fretrade (infretrade) is equal to 1 if the total number of insider trades are above (below) median and we interact it with the connect dummy. This result is reported in column (2) of table 6. The coefficient on the connect dummy is significantly negative only when insiders trade less frequently through this connected brokerage house. The second 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. Column (3) of table 6 reports the result. The coefficient on connect dummy is two times larger when the average trade size is above median. This supports our hypothesis that connected analysts extract more useful signal from insider trades when the size of the trades is large. Overall, then, we find that larger and less frequent trades give a bigger edge to the inside analyst.

3.3.3 Analyst characteristics and forecast accuracy of connected analysts

Our hypothesis is that analysts employed at the inside broker obtain non-public information on insider trades through their relationship with the people who work for the brokerage trading desks in her company. 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 talk to the 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. The result is reported in column (1) and (2) of table 7. Consistent with our hypothesis, the coefficient on 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 time taken to develop a relationship within a firm.

The second analyst characteristic we examine is the complexity of the connected analyst's coverage portfolio. Clement (1999) argues that analysts have deeper knowledge and insights on a specific firm when she has a less complex portfolio 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 was considering an acquisition in India might be able to infer its progress. If the analyst did not know this information, this inference would not have been possible. We thus expect the information our connected analysts get access to will be more useful when the analyst has a simpler portfolio of stocks to cover. Following Clement (1999), we use the number of stocks covered by this analyst as a proxy for portfolio complexity. We create a dummy, complexport, equal to 1 when the number of stocks covered is above median and interact with the connect dummy. The result is reported in column (3) of table 7. The coefficient on the connect_simpleport dummy is -0.105 (t=-2.99), implying a 14.4% reduction in error, while the connect_complexport dummy is -0.054 (t=-1.66, a 7.3% reduction relative to sample mean). These results support our 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 effect, so we are essentially comparing the forecast accuracy for 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 use exploit any information edge within her reach to improve upon her forecast.

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 firm 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 below median ranking of forecast error. We then regress PAFE on the interaction term between connect and our analyst skill dummy, and report the result in column (4) of table 7. 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 are able to 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 analysts who are geographically co-located with their trading desk colleague would perhaps have a closer relationship with him, enabling them 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 MSA area. We use insider's location to proxy for broker's location since for insiders location information is available, 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 column (5) of table 7. The coefficient on the connect dummy is 3.5 times as large when the analyst and insider are from the same MSA area, as compared to when they are not located in the same city. This supports our premise that geographic proximity facilitates the information flow between the connected analyst and their trading desk colleague who passes the information.

Finally, we show that this last result 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 takes this into account, if such advantage arises especially at the times 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 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.

3.4 Market reactions to connected analyst recommendation changes

Given that connected analysts are more accurate, one natural question that 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 may not reflect the market understanding that they are differentially informed only at specific and predictable times – when an insider has traded through their 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 other analysts but measured *in periods when she is not informed*. Finally we examine the difference-in-difference of the market reaction (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 8 for upgrades and Panel B for downgrades.

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

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

$$CAR\ (-1, +1) = b * connect + c * recom\_age + e \qquad (3)$$

We get similar results as above using this specification, which we present in the Appendix.

Overall, this suggests that the market identifies that inside analysts are *on average* more informed. To see this, note that connected analyst 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 show that the connected analyst's recommendation is indeed more valuable (from an investment point of view) in periods following insider trades, relative to all other periods.

3.5 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 understand, we examine 3-day earnings announcement returns in the first quarter following the recommendation change. We focus on earnings announcement day return 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 consensus view (positive) and those less favorable than consensus view (negative). The result is reported in table 9. For the average connected analyst whose recommendation is more positive than consensus, the 3-day CAR around the subsequent quarterly earnings announcement is 0.83%. However, the 3-day CAR around earnings announcements for the same analysts 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.

Notice however that since profits are strong only on the short leg, when the inside analyst 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 analyst recommendations, but short-sale frictions prevent it from trading all such profits away. While we cannot completely rule this out, this seems less likely in the light of our results in the previous section (market reacts similarly to recommendation changes of inside analysts in periods following and not following insider trades), and also in the light of the fact that the stocks we consider are those covered by 2 analysts on average, and hence typically larger (even with the inside analyst advantage being stronger among smaller stocks in our sample, note that a firm in the 25th percentile of our sample still has market-cap of $759 million, and is covered by 2 analysts). Such stocks are unlikely to have binding short-sale constraints.

3.6 Forecast accuracy versus optimism

One problem with interpreting 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 connect dummy to be significantly positive. Table 2 in Appendix reports the regression result. As we can see, the coefficient on connect dummy is negative and insignificant, so the result does not support the alternative explanation that connected analysts are less optimistic.[8]

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

3.7 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 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 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 |P12-TP|/P, where P12 is the stock price 12 months following 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 10. 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 1% level. The mean absolute forecast error on target price across our sample of analysts who are connected to a firm at some period, but not connected currently is 49%[9], so connected analysts on average reduce forecast error on target price by 2% relative to the mean. 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 compared to 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 more related to earnings rather than stock prices directly.

3.8 Long-horizon Earnings Forecast Accuracy

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

The information contained in insider trades could either be short- or long-lived. Our analysis so far mainly looks at whether inside analysts use information from insider trades to improve one-year ahead earnings forecast, as the one-year ahead earnings forecast is usually the focus of the analyst forecast literature. However, analysts also produce two-year ahead EPS forecasts, and in some cases, a long-term growth rate forecast. In this section, we test whether connected analysts also forecast more accurate two-year ahead earnings, and the long-term growth rate.

We control for the same set of paired fixed effects in these long-horizon tests as we do for our baseline regression. Specifically, two-year ahead earnings forecast error is defined as the absolute value of an analyst's latest forecast for FY2 EPS, 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 connect dummy is equal to 1 for an analyst issuing an earnings forecast on a stock following the firm insider's trade through the brokerage house employing this analyst. The result is reported in column 1 of Table 11. The coefficient on the connect dummy is -0.028, and significant at the 10% level. The mean percentage absolute forecast error for FY2 EPS across our sample of analysts who are connected to a firm at some period, but not connected currently, is 2.45%, so connected analysts on average have 1.1% smaller forecast error compared to the sample mean forecast error. The result indicates that inside analysts' information advantage in forecasting long-horizon earnings is much more limited compared to forecasting short-horizon earnings.

We also examine whether inside analysts forecast more accurate long-term growth rate. Forecast error on long-term growth rate is defined as the absolute value of forecasted long-term growth minus actual five-year long-term growth rate starting from the forecast year. We measure actual long-term growth following Dechow and Sloan (1997) and I/B/E/S methodology.[10] If actual EPS is negative, we omit that observation from the regression, and we require a minimum of three years of nonnegative EPS to estimate the regression. The result is reported in column (2) of Table 11. The coefficient on the connect dummy is -0.52 and significant at 10%. The mean percentage absolute forecast error on long-term growth rate (in percentage) across our sample of analysts who are connected to a firm at some period, but not connected currently is 16.75, so connected analysts on average have 3.1% smaller forecast error on long-term growth rate compared to the sample mean forecast error.

[10] Dechow and Sloan (1997) argue that discrete annualized geometric growth rates can be extremely volatile when the base year is close to zero and when the base year or final year in the series contains significant nonrecurring items. Computing five-year annualized growth rates by fitting a least squares growth line to the logarithms of the annual earnings observations avoids extreme outliers due to discrete compounding and avoids placing excessive weight on the first and last observations in the growth series, particularly when there could be substantial nonrecurring items.

Overall, our results suggest that the inside analysts' information advantage also extends to forecasting slightly more accurate long-horizon earnings and earnings growth rates, but the effect is much less pronounced compared to short-horizon earnings forecasts, both economically and statistically.

3.9 Robustness Checks

In this section, we conduct more robustness tests on our baseline regression. We report these results in table 12. First, we winsorize our dependent variable PAFE at different thresholds. In Column (1), we winsorize PAFE at 0.5% and 99.5% level. In Column (2), we winsorize PAFE at 2% and 98% level. 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, respectively, one quarter, 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 because a connected analyst may not revise her earnings forecast when the information she obtains from insider trades is consistent with her forecast issued before insider trading date. In this case, the connected analysts' forecast should still be more accurate than 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 additional control variables: forecast frequency, and firm-specific relative experience, which have been shown by 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 we can see from column (6), our result does not change with these two additional controls.

4. The inside broker's information advantage: channels

We gave an example in the introduction on the nature of the trading instruction – limit order vs. market – being one potential source of information advantage of the inside broker. Clearly, however, this is not the only source of information advantage that the inside broker can acquire. Many other channels could also convey similar information to the broker: 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 – in possession of the broker purely incidentally, which again the market would not have – could also be helpful in inferring whether the trade was more likely due to liquidity reasons or information driven.

In addition, the broker might become aware of other kinds of information in the process of his interaction with the insider, such as whether the sale was motivated by a desire to purchase some asset, like a house or a yacht. It is also possible that the broker 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 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 be useful to understand the motives behind the trade better than anyone else.

To make our case stronger, there is even testimonial evidence in favor of at least one of the channels we mentioned in this section – 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.

4.1 A test of a channel

In general it is difficult to show definitive evidence of what the broker might know which 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. The only thing we could do is to look for evidence of the following nature: something that becomes clear to non-connected analysts in the future, but the inside analyst could have known this earlier, i.e., at the time of the trade itself.

One example is the start of a trading pattern. Suppose the insider starts trading in the same month every year. This would become clear to others only in the future after a few trades. However, it is possible that the broker would have known that this was the insider's plan right when he implements the first or second trade according to the pattern. In this section, we test whether the connected analyst's forecasts following the beginning of a regular pattern of insider trades is associated with more informative forecasts compared to the same connected analyst's forecasts towards the end of a regular trading sequence (when the fact that it is a sequence trade becomes clear to everyone).

Specifically, we identify routine trades following Cohen, Malloy, and Pomorski (2013) as insider trades which 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 the routine trades, we further define three dummies differentiating between trades that occur for the first time in the sequence, second time in the sequence, and third or more years on in the sequence. We then regress our PAFE measure on the interaction between these four dummies with the connect dummy.

We report this result in Table 13. For routine trades, the magnitude of 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 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[11]. Since only the connected analyst is likely know that the first trade belongs to a regular trading pattern, their information advantage over non-connected analysts should be largest at such times. The result thus supports our conjecture that inside analysts indeed get information beyond that contained in the public disclosure of the trade itself.

This particular result also helps rule out an important alternative – that of reverse causality. The reverse causality argument would be that at certain points in time, the connected analyst has particular information or analysis advantage over everyone else. At these times she issues better forecasts, and also recommends the insider to trade.[12] So the effect we capture is spurious.

But here we show an example of a trade which is not particularly informed about anything at the firm, it is a first-in-sequence trade; yet, the inside analyst knows something more than the market. There is nothing here that she could know beyond the fact that this trade will be part of a sequence, and hence, while her compatriots who do not yet understand it is so might think it is informative, she knows it is *not*.

[11] There are 915 observations with connect_rtrade1 equal to 1, 961 observations with connect_rtrade2 equal to 1, 938 observations with connect_rtrade3 equal to 1 and 15,379 observations with connect_otrade equal to 1.

[12] Note first that under this alternative, there is no particular reason for the insider trade to always precede the forecast or recommendation change, but, still, we cannot rule out such an incidence.

In fact, it is this *lack* of informativeness of the trade that is her information advantage. This is not a trading idea that originated from the analyst.

5. Legality: a discussion

The 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 aspects: i) whether the analyst obtained material non-public information, and ii) whether the analyst selectively disclosed 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" 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 as 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 is 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 guesses, correctly, 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 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 would become better informed 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 is material, e.g., that the company is likely to announce large losses for the year, the behavior we document *per se* is not necessarily illegal. If the analyst does not herself trade on this information, and discloses this for the first time in her publicly disseminated report, then there is nothing illegal about it. This is because whenever someone does come in 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 in possession of information that is considered material and, before making this information public, she tips certain selective clients 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 violated her fiduciary duty when she passed on the information, the information was material and non-public, and she deliberately trades or passes this information further to obtain some (even non-monetary) benefit.

While we cannot differentiate between these two possibilities, our results point to an information advantage for the inside broker, and as discussed earlier, the possibility of other activities that will be considered illegal does remain, calling for – at least – more attention from insider trading law enforcement agencies.

6. 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. While insider trading laws, and their enforcement agencies in various countries focus closely on anyone involved professionally with any firm; and hence, in a position to glean private information – like lawyers, accountants etc., they ignore people professionally involved with firm insiders, whose job makes them just as likely to glean private information in the process of their interaction with the insider. One prime example is the stock broker through whom an insider trades.

We identify the stock broking house that firm insiders trade through from a form filed with the SEC, and show that analysts employed at such 'inside brokers' know better. These connected analysts' forecasts are significantly more accurate, compared to all other analysts – each of whom can, incidentally, observe the regulatory disclosure of the trade itself – and also more accurate compared to her own forecast in any period when the insider does not trade.

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

Since almost all traders, and not just corporate insiders, trade through brokers, the information advantage the broker enjoys in its role as a trading intermediary could be more general. For example, when an activist hedge fund is slowly acquiring shares in a company, her broker would have this information before any filing of 13D, which is when such information typically becomes public. Even after the knowledge of an activist hedge fund acquiring 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 commitment of the hedge fund – 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.

7. Appendix

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 amounts 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 volume of sale and holding period restrictions. The text of Rule 144 explains, 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 restricted securities of the issuer." Essentially, if the seller of a small number of unregistered securities isn't considered an underwriter, they are 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 below.

144 1 d99455d144.htm FORM 144

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

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

FORM 144

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

SEC USE ONLY
DOCUMENT SEQUENCE NO.
CUSIP NUMBER
WORK LOCATION

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

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

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

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

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

INSTRUCTIONS:

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

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

SEC 1147 (08-07)

8. References

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, Journal of Finance 56, 531-564.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2003, Reassessing the returns to analysts' stock recommendations, Financial Analysts Journal 59, 88-96.

Bettis, Carr, Don Vickery, and Donn W. Vickery, 1997, Mimickers of corporate insiders who make large-volume trades, Financial Analysts Journal 53, 57-66.

Bhattacharya, Utpal, and Hazem Daouk., 2002, The world price of insider trading, The Journal of Finance 57.1, 75-108.

Chen, Qi and Wei Jiang, 2006, Analysts' weighting of private and public information, Review of Financial Studies 19, 319-355.

Chen, T., Vidhi Chhaochharia and Rik Sen, 2014, Holding On for Good Times: The Information Content of CEOs' Voluntary Equity Exposure, Working paper, HKUST.

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

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010, Sell-side School Ties, Journal of Finance 65, 1409-1437.

Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, 2012, Decoding inside information, Journal of Finance 67, 1009-1043.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, Journal of Finance 57, 2113-2141.

Fama, E. F., & French, K. R., 1993, Common risk factors in the returns on stocks and bonds. Journal of financial economics, 33(1), 3-56.

Geczy, C., & Yan, J., 2006, Who are the beneficiaries when insiders trade? An examination of piggybacking in the brokerage industry, Working Paper, Wharton.

Gleason, Cristi A., and Charles M. C. Lee, 2003, Analyst forecast revisions and market price discovery, The Accounting Review 78, 193-225.

Glosten, L.R. and Milgrom, P.R., 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, Journal of Financial Economics, 14(1), 71-100.

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

Hong, H., & Kacperczyk, M., 2009, The price of sin: The effects of social norms on markets. Journal of Financial Economics, 93(1), 15-36.

Hong, H., & Kubik, J. D., 2003, Analyzing the analysts: Career concerns and biased earnings forecasts. Journal of Finance, 313-351.

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

Jaffe, Jeffrey, 1974, Special information and insider trading, Journal of Business 47, 410-428.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083-1124.

Kyle, A.S., 1985, Continuous auctions and insider trading, Econometrica, 1315-1335.

Lakonishok, Josef, and Inmoo Lee, 2001, Are insiders' trades more informative? Review of Financial Studies 14, 79-111.

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

Lin, Ji-Chai, and John Howe, 1990, Insider trading in the OTC market, Journal of Finance 45, 1273-1284.

Lorie, James, and Victor Niederhoffer, 1968, Predictive and statistical properties of insider trading, Journal of Law and Economics 11, 35-53.

W. McNally, A. Schkilko, and B. Smith, 2015, Do brokers of insiders tip other clients? Management Science, forthcoming

Malloy, Christopher, 2005, The geography of equity analysts, Journal of Finance, Vol. 60, No. 2 (April 2005), 719-755.

Marin, Jose, and Jacques Olivier, 2008, The dog that did not bark: Insider trading and crashes, Journal of Finance 63, 2429-2476.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does forecast accuracy matter to security analysts? The Accounting Review 74, 185-200.

Ramnath, Sundaresh, Steve Rock, and Philip Shane, 2008, The financial analyst forecasting literature: A taxonomy with suggestions for further research, International Journal of Forecasting 24, 34-75.

Rozeff, Michael, and Mir Zaman, 1988, Market efficiency and insider trading: New evidence, Journal of Business 61, 25-44.

Scott, J., & Xu, P., 2004, Some insider sales are positive signals, Financial Analysts Journal, 60(3), 44-51.

Seyhun, H. Nejat, 1986, Insiders' profits, costs of trading, and market efficiency, Journal of Financial Economics 16, 189-212.

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

Sun, L. and K.C. John Wei, 2011, How Does Competition Affect Opinion Dispersion? Working paper, HKUST.

Stickel, Scott E., 1991, Common stock returns surrounding earnings forecast revisions: more puzzling evidence. The Accounting Review, 66, 402- 416.

Stickel, Scott E., 1992, Reputation and performance among security analysts, Journal of Finance 47, 1811-1836.

Womack, Kent, 1996, Do brokerage analysts' recommendations have investment value? Journal of Finance 51, 137-167.

Table 1: Form 144 trades

This table 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.

	No.of obs	**Mean**	**p10**	**Median**	**p90**
Number of insiders per company	11380	18	1	9	40
Number of trades per company	11380	52	1	18	140
Number of insiders per company-year	59462	6	1	3	11
Number of trades per company-year	59462	10	1	5	23
Number of shares traded per trade	591715	149676	1000	10036	100000
Number of shares traded per trade (% of shares outstanding)	591715	0.758%	0.002%	0.026%	0.286%
Value of shares traded per trade	591508	3056155	18000	250620	2690000
Value of shares traded per trade (% of market cap)	591508	0.774%	0.002%	0.026%	0.026%
Number of shares traded per company-year	59462	1489446	6750	109382	109382
Number of shares traded per company-year (% of shares outstanding)	59462	7.538%	0.024%	0.385%	3.302%
Value of shares traded per company-year	59452	30406714	64477	1633965	29549000
Value of shares traded per company-year (% of market cap)	59452	7.717%	0.024%	0.391%	3.389%

Table 2: 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. 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 occurred during the period from 1 year prior to earnings announcement to 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 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 month's 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 past six months. Residual analyst coverage (rcoverage) is the residual from 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 for which the analyst has worked at this brokerage house up to the current year. Number of firm 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. Panel C reports the summary statistics for the entire Compustat sample for the same sample period. In panel D, 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 the return on either the market (market adjusted) or Size-Book-to-market-Momentum matched portfolio (DGTW adjusted). Recom_age is the log number of days between recommendation announcement day and the most recent earnings announcement day.

Panel A: full sample

Variables	No.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 B: Connected forecast sample

Variables	No.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 C: Pseudo-connect sample

Variables	No.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 D: Compustat sample

Variables	No.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%
disp	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 E: Recommendation Sample

	Variables		N.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%

Table 3: Forecast accuracy of the analyst affiliated with the inside broker

This table reports result 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 effect. In column (2), we control for broker-firm and firm-year fixed effect. In column (3), we control for firm-year and analyst-broker-firm fixed effect. In column (4), we control for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. In column (5), we control for an affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effect. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level 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
Ave.R-sq	0.344	0.904	0.916	0.929	0.929
N.of Obs.	499459	438393	383659	370578	370578

Table 4: Falsification Tests

This table reports the results of three falsification tests. In column (1) and (2), we consider that analysts changes job but still covers the same firm. Specifically, we create a pseudo connect dummy equal to one 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 column (3) and (4), we firm insiders who change their broker but stay at the same firm. Specifically, we create a pseudo dummy equal to one 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 column (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 one 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. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level 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 his 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
Ave.R-sq	0.929	0.929	0.929	0.929	0.929	0.929
N.of Obs.	370580	370580	370578	370578	370578	370578

Table 5: Firm characteristics and forecast accuracy of the inside analyst

This table reports result of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy interacted with various firm characteristics, an affiliation dummy and forecast age, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. In column (1), connect_smallfirm (connect_bigfirm) is the interaction of connect dummy with a dummy indicating below (above) median market capitalization. In column (2), connect_highvol (connect_lowvol) is the interaction of connect dummy with a dummy indicating above (below) median monthly stock return volatility. In column (3), connect_highdisp (connect_lowdisp) is the interaction of connect dummy with a dummy indicating above (below) median analyst forecast dispersion. In column (4), connect_highturn (connect_lowturn) is the interaction of connect dummy with a dummy indicating above (below) median monthly turnover. In column (5), connect_highcov (connect_lowcov) is the interaction of connect dummy with a dummy indicating above (below) median analyst coverage. In column (6), connect_highrcov (connect_lowrcov) is the interaction of the connect dummy with a dummy indicating above (below) median residual analyst coverage. In column (7), connect_growth (connect_value) is the interaction of the connect dummy with a dummy indicating above (below) median B/M ratio. In column (8), connect_highrd (connect_lowrd) is the interaction of connect dummy with a dummy indicating above (below) median R&D intensity. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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_highrcov						-0.1320**		
						(-2.05)		
connect_lowrcov						-0.0585**		
						(-2.25)		
connect_growth							-0.0955**	
							(-2.32)	
connect_value							-0.0404	
							(-1.38)	
connect_highrd								-0.1718***
								(-2.60)
connect_lowrd								-0.0664**
								(-2.35)
fore_age	0.0507***	0.0507***	0.0507***	0.0507***	0.0506***	0.0506***	0.0507***	0.0506***
	(6.00)	(6.01)	(6.00)	(6.01)	(6.00)	(6.00)	(6.00)	(6.00)
affil	-0.1607	-0.1611	-0.1640	-0.1621	-0.1603	-0.1639	-0.1614	-0.1620
	(-1.42)	(-1.42)	(-1.45)	(-1.43)	(-1.41)	(-1.45)	(-1.43)	(-1.43)
Ave.R-sq	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
N.of Obs.	370578	370578	370578	370578	370578	370578	370578	370578

Table 6: Trade characteristics and forecast accuracy of the inside analyst

This table reports result of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy interacted with various insider trade characteristics, an affiliation dummy and forecast age, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. In column (1), connect_preFD (connect_postFD) is the interaction of connect dummy with a dummy indicating pre (post) Regulation Fair Disclosure period. In column (2), connect_infretrade (connect_fretrade) is the interaction of connect dummy with a dummy indicating the total number of insider trades occurred during the period specified for the connect is less (more) than 5. In column (3), connect_smalltrade (connect_bigtrade) is the interaction of connect dummy with a dummy indicating below (above) median average trade size. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	(1)	(2)	(3)
connect_preFD	0.0056		
	(0.23)		
connect_postFD	-0.0968***		
	(-2.95)		
connect_infretrade		-0.0795***	
		(-2.80)	
connect_fretrade		-0.0508	
		(-1.05)	
connect_smalltrade			-0.0454
			(-1.63)
connect_bigtrade			-0.1166***
			(-2.98)
fore_age	0.0506***	0.0506***	0.0507***
	(6.00)	(6.00)	(6.00)
affil	-0.1624	-0.1626	-0.1609
	(-1.43)	(-1.44)	(-1.42)
Ave.R-sq	0.929	0.929	0.929
N.of Obs.	370578	370578	370578

Table 7: Analyst characteristics and forecast accuracy of the inside analyst

This table reports result 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 effect. In column (1), connect_early2 (connect_late2) is the interaction of connect dummy with a dummy indicating the analyst is within (beyond) first *two* years of joining the brokerage firm. In column (2), connect_early3 (connect_late3) is the interaction of connect dummy with a dummy indicating the analyst is within (beyond) first *three* years of joining the brokerage firm. In column (3), connect_complexport (connect_simpleport) is the interaction of connect dummy with a dummy indicating the number of stocks covered by the analyst this year is above (below) median. In column (4), connect_highskill (connect_lowskill) is the interaction of connect dummy with a dummy indicating the analysts' average ranking of forecast accuracy is above (below) median. In column (5), connect_sameloc (connect_nsameloc) is the interaction of connect dummy with a dummy indicating the analyst and insider located in the same MSA area. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
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_complexport			-0.0543*		
			(-1.66)		
connect_simpleport			-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)
fore_age	0.0506***	0.0505***	0.0507***	0.0506***	0.0507***
	(5.99)	(5.99)	(6.00)	(5.99)	(6.00)
affil	-0.1627	-0.1628	-0.1627	-0.1624	-0.1621
	(-1.44)	(-1.44)	(-1.44)	(-1.43)	(-1.43)
Ave.R-sq	0.929	0.929	0.929	0.929	0.929
N.of Obs.	370578	370578	370578	370578	370578

Table 8: Market reaction to recommendation changes of 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 analysts who is employed by a brokerage where firm insiders trade through and the announcement date is within 1 year following insider trade date. Pseudo connection is defined as recommendations issued by analysts who is connected with the firm at some point of time but not in current period. The control sample is the never connected analysts who covers 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 portfolio (DGTW adjusted). 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: Upgrade

Market adjusted	Connect	Control	Connect minus control	Pseudo-connect	Control	Pseudo-connect minus control	Diff-in-Diff
CAR(-1,+1)	3.19%	2.33%	0.86%	2.89%	2.40%	0.49%	0.37%
t-stat	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%
t-stat	13.16	10.56	2.88	13.99	12.94	2.93	0.19

Panel B: Downgrade

Market adjusted	Connect	Control	Connect minus control	Pseudo-connect	Control	Pseudo-connect minus control	Diff-in-Diff
CAR(-1,+1)	-4.10%	-2.89%	-1.21%	-2.66%	-2.05%	-0.61%	-0.60%
t-stat	-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%
t-stat	-13.32	-11.74	-3.82	-11.85	-11.26	-2.8	-1.10

Table 9: Earnings Announcement Returns Following Analysts' Recommendation Change

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 analysts who is employed by a brokerage where firm insiders trade through and the announcement date is within 1 year following insider trade date. Pseudo connection is defined as recommendations issued by analysts who is connected with the firm at some point of time but not in 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 portfolio (DGTW adjusted). In panel A, we report the results for recommendations that are above prevailing consensus recommendation and in panel B, we report the results for recommendations that are below prevailing consensus. Recommendation initiations are excluded from this sample. The sample period is from 1997 to 2013.

Panel A: Recommendation > Consensus			
Market adjusted	connect	pseudo connect	connect-pseudo
CAR(-1,+1)	0.83%	0.87%	-0.04%
t-stat	4.03	4.29	-0.13
DGTW adjusted			
CAR(-1,+1)	0.65%	0.74%	-0.09%
t-stat	3.31	3.90	-0.34

Panel B: Recommendation < Consensus			
Market adjusted	connect	pseudo connect	connect-pseudo
CAR(-1,+1)	0.16%	0.72%	-0.56%
t-stat	0.82	3.87	-2.10
DGTW adjusted			
CAR(-1,+1)	0.03%	0.56%	-0.52%
t-stat	0.19	3.18	-2.07

Table 10: Target Price Forecast Accuracy of the insider analyst

This table reports result 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 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 1% and 99% level. We control for an affiliation dummy and analyst-broker-firm, analyst-broker-year and firm-year fixed effect. 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 * stands for significance level 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
Ave.R-sq	0.921
N.of Obs.	1008458

Table 11: Long-horizon Earnings Forecast Accuracy of the insider analyst

This table reports result of the panel regression of analyst absolute forecast error of two-year ahead EPS (column 1) and long-term growth rate (column 2) on the connect dummy. Two-year ahead earnings forecast error is defined as the absolute value of an analyst's latest forecast for FY2 EPS, 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. Forecast error on long-term growth rate is defined as the absolute value of forecasted long-term growth minus actual five-year long-term growth rate starting from the forecast year. Following Dechow and Sloan (1997) and I/B/E/S methodology, actual long-term growth is measured as the slope from a regression of log(EPS) on a time trend over a five-year period beginning in the forecast year. If actual EPS is negative, we omit that observation from the regression, and we require a minimum of three years of nonnegative EPS to estimate the regression. We control for an affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effect. The definition of all the control variables are in table 2. The sample include 408,339 two-year ahead EPS forecast from 1997 to 2013 and 111,632 long-term growth rate forecast from 1997 to 2009. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	FY2 EPS	LTG
connect	-0.0278*	-0.5172*
	(-1.78)	(-1.82)
fore_age	0.8290***	0.0623
	(18.78)	(1.18)
affil	0.0393	0.8309
	(0.84)	(1.25)
analyst-broker-firm FE	yes	yes
analyst-broker-year FE	yes	yes
firm-year FE	yes	yes
Ave.R-sq	0.967	0.983
N.of Obs.	312369	46100

Table 12: Robustness

This table reports various robustness checks of the baseline regression. In Column (1), we winsorize the percentage absolute forecast error (PAFE) at 0.5% and 99.5% level. In Column (2), we winsorize the percentage forecast error (PAFE) at 2% and 98% level. In column (3) and (4), we use the stock price one month and one quarter before earnings announcement date to scale forecast error, respectively. 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 addition 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 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level 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
Ave.R-sq	0.943	0.923	0.953	0.950	0.929	0.930
N.of Obs.	370672	370672	381745	382552	370672	364922

Table 13: Forecast accuracy of the inside analyst following routine/opportunistic trades

This table reports result of the panel regression of percentage analyst absolute forecast error (PAFE) on the connect dummy interacted with four dummies indicating routine or opportunistic insider trades. Following Cohen et al. (2013), routine trades are those occurred in the same calendar month of three consecutive years. Connect_1st_in_seq is the interaction of the connect dummy with a dummy indicating first-year routine trade. Connect_2nd_in_seq is the interaction of the connect dummy with a dummy indicating second-year routine trade. Connect_late_in_seq is the interaction of the connect dummy with a dummy indicating routine trade in third year or beyond. Connect_nonroutine is the interaction of the connect dummy with a dummy indicating opportunistic trades. The definition of all the control variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. We control for forecast age, an affiliation dummy, analyst-broker-firm, analyst-broker-year and firm-year fixed effect in the regression. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	(1)
connect_1st_in_seq	-0.1044*
	(-1.67)
connect_2nd_in_seq	-0.0585
	(-0.86)
connect_later_in seq	0.0201
	(0.37)
connect_nonroutine	-0.0692***
	(-2.59)
fore_age	0.0507***
	(6.00)
affil	-0.1622
	(-1.43)
firm-year FE	yes
analyst-broker-firm FE	yes
analyst-broker-year FE	yes
Ave.R-sq	0.929
N.of Obs.	370578

Appendix Table 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 short the stocks with form 144 trades in the past one month and long all other stocks. The portfolio is monthly re-balanced. We report both the equal-weighted and value-weighted monthly excess returns, as well as Fama-French 3-factor alpha and Carhart (1997) 4-factor alpha. In panel B, we run Fama-MacBeth regression of next month return on 3 different measures of form 144 trades, and controlling for other common cross-sectional stock return predictors. In Column (1), form 144 sell is a dummy equals one 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 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. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

Panel A: Calendar Time Portfolios

	Form144 Stocks	Other Stocks	Others - Form144
		Equal-weighted Portfolio	
Excess Return	0.52%	1.13%	0.61%
	(1.08)	(2.60)	(3.63)
FF 3-factor alpha	-0.27%	0.31%	0.57%
	(-1.86)	(1.76)	(4.30)
FFC 4-factor alpha	-0.17%	0.47%	0.64%
	(-1.31)	(3.37)	(4.99)
		Value-weighted Portfolio	
Raw Return	0.11%	0.47%	0.36%
	(0.26)	(1.33)	(1.72)
FF 3-factor alpha	-0.18%	0.10%	0.27%
	(-1.75)	(2.01)	(1.96)
FFC 4-factor alpha	-0.21%	0.12%	0.33%
	(-2.12)	(2.56)	(2.42)

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
N.of Obs.	1094876	1094876	1094876

Appendix Table 2: Forecast accuracy of the inside analyst (fixed sample)

This table reports result 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 effect. In column (2), we control for broker-firm and firm-year fixed effect. In column (3), we control for firm-year and analyst-broker-firm fixed effect. In column (4), we control for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. In column (5), we control for an affiliation dummy, forecast age, and analyst-broker-firm, analyst-broker-year and firm-year fixed effect. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level 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
Ave.R-sq	0.330	0.907	0.916	0.929	0.929
N.of Obs.	370578	370578	370578	370578	370578

Appendix Table 3: Forecast Accuracy versus Optimism

This table reports the regression results of the signed percentage analyst forecast error (PFE) on connect dummy, an affiliation dummy and forecast age, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. The definition of all the variables are in table 2. The sample includes 600,686 earnings forecasts from 1997–2013. Standard errors are clustered by firm, and t statistics are reported below each estimate. ***, **, and * stands for significance level 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
Ave.R-sq	0.886
N.of Obs.	370578

Appendix Table 4: Market reaction to recommendation changes of the inside analyst

This table reports results of regression of cumulative abnormal returns following recommendation change on the connect dummy, controlling for analyst-broker-firm, analyst-broker-year and firm-year fixed effect. The dependent variable is the 3-day cumulative abnormal returns CAR (-1, +1) around 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 portfolio (DGTW adjusted). The definition of all the variables are 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 * stands for significance level of 1%, 5% and 10%, respectively.

	Market-adjusted		DGTW-adjusted	
	CAR (-1 ,+1) upgrade	CAR (-1 ,+1) downgrade	CAR (-1 ,+1) upgrade	CAR (-1 ,+1) 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
Ave.R-sq	0.555	0.559	0.547	0.558
N.of Obs.	6926	8455	6926	8455