Inside Brokers

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ABSTRACT

We identify the stock broking house that firm's 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. This advantage of the "inside analyst" is stronger for firms that are smaller, more opaque, and with greater disagreement about their future. Unlike many other sources of analyst comparative advantage, the effect we show is stronger after Regulation Fair Disclosure. We show that one source of advantage of the broker is the knowledge of the nature of the trading instruction, which facilitates inference about the trade's information content. Our results have important implications for regulations needed to deal with information asymmetry that arises from the process of trading by insiders.

JEL: G24, G30, G34, G38

Keywords: Insiders, Brokers, Analysts, Information Transmission

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We identify the stock broking house that firm's 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. This advantage of the "inside analyst" is stronger for firms that are smaller, more opaque, and with greater disagreement about their future. Unlike many other sources of analyst comparative advantage, the effect we show is stronger after Regulation Fair Disclosure. We show that one source of advantage of the broker is the knowledge of the nature of the trading instruction, which facilitates inference about the trade's information content. Our results have important implications for regulations needed to deal with information asymmetry that arises from the process of trading by insiders.

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1. Introduction

The ability to trade securities at a relatively low cost is critical for the efficient absorption of information into asset prices, and hence, for efficient functioning of the financial system. But liquidity providers – who facilitate such trading – face the risk of being adversely selected against if some other market participants are endowed with asymmetric "inside" information (Kyle (1985), Glosten and Milgrom (1985)). This is an important issue, since the resultant loss in liquidity makes stock traders require higher return on equity, and consequently affects the cost of capital, and hence, growth of public companies (Bhattacharya and Daouk, 2002). This is the theoretical motivation behind insider trading laws and other regulations that try to keep adverse selection concerns of market participants under control. Such laws typically recognize explicitly that corporate insiders, auditors, consultants, and lawyers, through the very nature of the activities they are involved in, can become asymmetrically informed. All of these have relationships with the firm and therefore have an obvious fiduciary duty exactly like an insider.

However, there are other participants who can get asymmetrically informed through firm insiders – in much the same way that the theory is worried about – which the law *does not* recognize very clearly. In this paper we look at one such group – the stock broker through whom firm insiders trade.

Insiders, by definition, have favored access to private information about their firm. There is a large literature showing that insiders are able to trade on their private information, to their own benefit. However, the law requires that insiders reveal these trades publicly within a short time window, to limit information asymmetry. The question we ask in this paper is whether this disclosure of the trade is sufficient in eliminating information asymmetry arising from the insider trading process? This is a very important question because the current regulatory regime operates under that assumption, so any answer in the negative makes a case for redesigning it.

Here we find evidence that the answer is indeed in the negative. We show that during the trading process, some relatively long-lived information advantage – *beyond that contained in the public disclosure of the trade itself* – passes to the broker used by the insider. The equity analyst employed by the broker who covers the insider's firm is able to benefit from this and make more accurate earnings forecasts, *even after the occurrence of the trade itself becomes public knowledge*.

Equity analysts are very likely to follow the publicly disclosed trades of insiders at the companies they cover. Some of these filings reveal which brokerage firm the insider used for the trade. When an analyst realizes that her own firm acted as the broker for the trade, given her incentive to generate better research reports, she might talk to her colleague who interacted with the insider and glean something that is potentially useful to her.[1]

To cite one example of why the broker might have an information advantage, he would definitely know the exact nature of the trading instruction and when it was given. For instance the trade could have been executed because of a limit order placed months in advance, or it could have been a market order which the insider wanted executed within the next few hours. 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 has been publicly disclosed. We list more examples on distinct sources of the inside broker's information advantage in Section 4.

Some of the sales of company shares by insiders (specifically, 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 investigate whether any information flows to the equity analyst employed by the broking house covering the company to which the insider belongs. We find that an analyst covering a firm gives more accurate forecasts of annual earnings after the insider has traded, relative to her own forecast accuracy at other times for the same firm. Since these forecasts are made after the

[1] We refer to the broker through whom the insider trades as the inside broker, and the affiliated analyst as the inside analyst or connected analyst in the following.

information on the trade has been made public through SEC filings by the insider, our result suggests that the broker obtains information beyond the knowledge of the trade itself. Note that this does not necessarily mean that analysts obtain material nonpublic information in violation of Regulation FD. Analysts could be piecing together public information and non-material information from management, and this is permitted by Regulation FD.

We exploit our panel data structure to help identify a causal link of our interest. The unit of observation is at the analyst-broker-firm-time level – the most updated forecast given by an analyst, working at a particular brokerage, for 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 pairwise combinations 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 the effect of our interest comes from earnings forecasts of a specific analyst at the insider's broker showing higher accuracy in the period after the trade, relative to her forecasts in other periods for the same firm. As a result, unobservables that are invariant at the broker-analyst-firm level do not affect our inference. One such example is social ties between a particular analyst and an insider can lead better forecasts (e.g., Cohen, Frazzini and Malloy, 2010) and the insider could choose the analyst's employer as her broker. 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 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 varies at 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.

We show that our main result – higher forecast accuracy of the forecast by the analyst at insider's broker after a trade (hereafter, connected analyst), is also robust to specifications that do not control as aggressively for unobserved heterogeneity and have fewer fixed effects. We then return to our stringent specification that aggressively controls for unobserved heterogeneity to examine when our main results are stronger. We find that the advantage of the connected analyst is greater for firms whose stocks trade under worse information environment: smaller firms, firms with higher return volatility, higher Tobin's *Q*, those with higher dispersion of analyst forecasts, and firms with higher R&D expenses. We find evidence that the effect is stronger for firms that have more analysts after controlling for firm size. This is consistent with analysts having greater incentives to gather information from all sources especially when they face greater competition. We also find that the advantage of connected analyst is greater following insider trades that are larger and more infrequent. An analyst who has just joined a brokerage firm may take some time to figure out who are the brokers of various insiders that are her firm's clients and establish a relationship with them. Consistent with this, we see the advantage of the connected analyst shows up strongly only two or three years after she joins a new brokerage firm. Similarly, obtaining information would be 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 leading to stronger effect of insider trade on forecast accuracy in these cases. We find evidence consistent with this.

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 all analysts could have preferential access to insiders through various channels. This was banned by Reg FD. After that the unique channel of information flow that the connected analyst has, because of being at the insider's brokerage firm, becomes more advantageous.

Next, we examine the market reaction to recommendation changes by connected analysts compared to other analysts. We find that in general there are greater price reactions in response to recommendation changes by connected analysts, but no differently in periods after an insider trades through her brokerage and the connected analyst is better informed. We then examine return predictability based on the value of the "inside broker" link. We construct a trading strategy, where we go long on all firms on which the connected analyst is more positive than the consensus. We then implement this strategy around a (-1,1) day window around the earnings announcement in the quarter following the recommendation change. As a benchmark, we consider those quarters when the same analyst is more positive than the consensus, but wasn't better informed as there was not trade by an insider. We examine a similar strategy for the short size, by going short on stocks where the connected analyst is more negative than the consensus. We find a statistically significant abnormal return of -0.56% when the connected analyst is more negative than the consensus, but fail to find such an effect then they are more positive. Overall, these results are consistent with the view that the market does not fully recognize that connected analysts are in a better position to draw inference about informed trading at times when an insider trades through their brokerage. Further, the results indicate that negative opinions by connected analysts are especially informative.

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. Specifically, 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 public data itself.

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 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 information 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: the inside analyst's information is strongest for first-in-sequence, weaker for second-in-sequence, and even more weak for all further-in-sequence trades. Of course, the inside analyst also has significant information advantage on the irregular (not-in-a-sequence) trades as well.

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 broker of insider 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 trade of the insider. The results of these papers imply that brokers have an information advantage *before* the information that the insider has traded becomes publicly available. This is not too surprising, and one might expect that such information advantage would dissipate when the trade of the insider is revealed publicly. In contrast, our study shows that brokers retain an information advantage even *after* the trade of the insider becomes public, which implies that some information beyond that contained in the trade disclosure itself passes to the inside broker.

The rest of the paper is organized as follows. Section 2 describes our data sources, 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. We explain the details of the background of the regulations that require such filings and the nature of the information in these forms in the Appendix. We manually standardize the broker names reported by different insiders and map this to I/B/E/S brokers. The five most common brokers of insiders by number of trades are Merrill Lynch, Citigroup, Morgan Stanley, Paine Webber, and Deutsche Bank Alex Brown. 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 nine 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 aggregate to median of 0.4% of the company's shares outstanding by all of its insiders.

3. Empirical Analysis

In this section, we investigate our main hypothesis, that is, the analyst employed by the brokerage firm through which a firm's insider has traded has an information advantage over other analysts when issuing earnings forecasts for that firm. We also examine when such connections would create stronger information advantage for the connected analysts.

3.1 Connected analysts and forecast accuracy

We measure forecast accuracy as the forecast error of analysts' annual EPS forecast. The percentage absolute forecast error (PAFE) for stock j at 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 the analyst's forecast is.

$$PAFE_{i,j,t} = 100 * |\text{Actual EPS}_{j,t} - \text{Forecasted EPS}_{i,j,t}| \; / \; \text{Price}_{j,\, t-1} \quad (1)$$

We run panel regressions of the percentage absolute forecast error on a connect dummy - our key explanatory variable, and control for various pairs of high-dimensional fixed effects.

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

The connect dummy is equal to 1 for 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 restrict the insider trades to be within one year before the annual earnings announcement date. In other words, we are examining whether the analyst issues more accurate earnings forecast on the stock when she is connected with the firm through the brokerage firm's trading desk who executes trades for the firms' managers. One concern is that the 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), perhaps due to the greater resources provided by large brokerage firms. The effect of the connect dummy on forecast accuracy could then be due to a brokerage effect, rather than the information obtained through affiliation with the insiders' broker. The common approach used by previous studies to mitigate this endogeneity concern is by adding various brokerage, analyst and firm characteristics that ex-ante could be correlated with forecast accuracy. In this paper, we use a different approach that relies on controlling for a rich set of interacted fixed effects for brokerage, analysts, firm and year. 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.

Table 3 reports the regression results. In column (1), we add firm, year and brokerage fixed effect. The coefficient on connect dummy is -0.15 in this specification and highly significant (t=-5.53). Consistent with our hypothesis, analysts are indeed more accurate when forecasting the firms' earnings when the firms' managers have traded through the brokerage that she works for during the past year. In column (2) and (3), we add paired fixed effect such as broker-firm and firm-year fixed effect. The coefficient on connect dummy is still significantly negative, although the magnitude is reduced by half. In column (4), we add a comprehensive set of paired fixed effect, including firm-year, analysts-broker-firm and analyst-broker-year fixed effect. 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 all other analysts following the same firm in the current fiscal year, to her own forecasts on other non-connected firms and her own forecasts issued on the same firm during other periods when the firm officers didn't trade through her brokerage firm.

Although our pairs of firm-year, analyst-broker-year and analyst-broker-firm fixed effect captures most of the analysts, brokerage and firm characteristics that may correlate with the connect dummy and affect forecast error, there are still some factors not fully captured by the fixed effect. 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. Connected analysts issue forecasts only after they see the insider trades, so it is possible that the age of connected forecasts are on average smaller than non-connected ones. Firm managers may 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 are more optimistic. 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 underwriting relationship between the analysts and the covered stock 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 report the result. First, we see that the coefficient on forecast age is significant 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 1% level. The economic magnitude of the relative forecast accuracy for the connected analysts is also quite large. The mean of the percentage absolute forecast error across our sample is 1.18%. The coefficient of -0.076 in the last column means connected analysts on average have 6.44% smaller forecast error compared to the sample mean forecast error.

3.2 Cross-sectional heterogeneity

Having confirmed our main hypothesis that connected analysts have an information advantage and provide more accurate earnings forecast over others, we next examine under what circumstances such information advantage would be most useful for the connected analysts. We examine various firm-level, trade-level and analysts characteristics that could amplify connected analysts' information advantage.

3.2.1 Firm characteristics and forecast accuracy of connected analysts

The first firm characteristic we look at is firm size, which is a proxy for firms' information environment. Small firms are less likely to be held by institutional investors and the number of analysts following small firms also tend to be fewer. Information diffusion speed is slower for smaller firms (Hong, Lim, and Stein 2000). Previous research documents that outsiders mimicking insider trades are more profitable among firms with smaller market capitalization (Lakonishok and Lee 2001). We thus expect the information obtained through the connection with the trading desk of brokerage firm 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 effect in this and all the remaining regressions. The result is reported in column (1) of table 4. Consistent with our prior, both the magnitude (absolute) and significance on the connect dummy is larger for small firms. The coefficient on connect_bigfirm is close to 0 and not significant, while that on small firm is -0.17 and highly significant (t=-3.49).

The private information obtained via insider trading transaction would be more useful for the connected analysts when there is more underlying uncertainty about the firms' future prospect. 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.[2] The results are reported in column (2) and (3) of table 4. Consistent with our hypothesis, we find the coefficient on the connect dummy is indeed more pronounced for firms with more volatile stock returns or dispersed opinion. For example, the coefficient on the connect dummy is -

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

0.15 (t=-3.03) 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' 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), but is much smaller in magnitude and not significant in low turnover stocks.

Analyst coverage is a commonly used proxy for firms' information environment. Firms with fewer 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 the forecast error on the interaction of connect dummy with a dummy indicating above or below median analyst coverage. Given the strong correlation between analyst coverage and size, we expect the connect dummy to be more pronounced among firms with fewer analyst coverage. This is indeed what we find. We also looked at residual analyst coverage in column (6), which is analyst coverage purged out of the size effect. We find the absolute magnitude of the connect dummy is larger in firms with high residual analyst coverage, although statistically they are similar. This result may be due to the competition effect. Since more analysts covering the same stock induce more competition (Hong and Kacperczyk 2010), this will leads to stronger incentive for the connected analyst to use the information contained in insider trading 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, and we expect insider information will be particularly useful for connected analysts among such stocks. The result is reported in column (7) of table 4. The coefficient of the connect dummy among growth stocks is -0.10 (t=-2.38), two times of that among value stocks.

The last firm characteristic we look at is R&D intensity. The rational is that firms with high R&D expenditures are high growth firms with little or no positive cash flows, and are inherently difficult to value. Analysts facing the challenging task of forecasting earnings of high R&D firms will benefit more from the information obtained through connection of insider trading. 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 4. Consistent with our hypothesis, the economic magnitude on the connect dummy is indeed more pronounced among the firms doing lots of R&D activities.

3.2.2 Trade characteristics and forecast accuracy of connected analysts

The information advantage of the connected analysts over other non-connected analysts crucially depends on how informative the connected insider trades are for future firm value. The insider trading literature has documented many interesting findings that not all insider trades are equally informative and we could screen out informative insider trades based on observable trades characteristics (Cohen, Malloy and Pomorski 2013; Scott and Xu 2004). In this section, we examine whether more informative insider trades lead to more accurate earnings forecast for connected analysts.

We first look at the total number of trades placed through the one year period up to analysts' earnings 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 5. The coefficient on the connect dummy is significantly negative only when insiders trade less frequently through this connected brokerage house. Cohen, Malloy and Pomorski (2013) find that routine insiders' trades are not informative while opportunistic insiders' trades are highly informative. To the extent that routine insiders trade more frequently, our results are consistent with the hypothesis that connected analysts provide more accurate forecasts only when the connected insider trades are informative.

The second trade characteristics we look at is the size of insider trades as a fraction of total shares outstanding. Larger trades are more likely to have information. In these cases, the broker of the insider, through her interactions, might be able to surmise whether they really do or not. To test this, we interact the connect dummy with a dummy indicating whether the mean trade size for connected insiders is above or below median. Column (3) of table 5 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.

After the passing 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 big 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 whether the information advantage the connected analysts have through brokerage-affiliated insider trading also disappears after Regulation FD. We expect this to be unlikely, because Regulation FD curtailed other channels of analysts of private access to management, while leaving the one that we explore relatively unaffected. Here, the manager is not necessarily consciously disclosing any information selectively to the connected analyst. The manager interacts with the trading desk and the analyst infers the information through them.

To test this, we define a time dummy postFD equal to 1 for all the analyst forecasts issued after year 2001, and interact it with the connect dummy. The result is reported in column (1). The connect_postFD has a coefficient of -0.097 (t=-2.95), 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 expected, since other non-connected analyst could also get access to private information through directly interacting with the firm's managers.

3.2.3 Analyst characteristics and forecast accuracy of connected analysts

Our hypothesis states that connected analysts obtain soft information of insider trades through creating a good relationship with the people who deal with the brokerage clients. But 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 hasn't yet established a strong relationship within 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 6. Consistent with our hypothesis, the coefficient on connect dummy is less pronounced and not significant when the analyst has worked this firm for less than two or three years. This result supports our earlier hypothesis about time taken to develop a relationship within a firm.

The second analyst characteristic we look at in this paper is the portfolio complexity of the connected analyst's coverage. Clement (1999) argues that analysts will have more deep knowledge and insights on a specific firm when the analyst have less complex portfolio to cover. We argue that this kind deep knowledge is also crucial for the connected analysts to correctly infer the information contained in insider trades. 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 6. The coefficient on the connect_simpleport dummy is -0.105 (t=-2.99), while the connect_simpleport dummy is -0.054 (t=-1.66). The result support our hypothesis that being focused helps the connected analysts better interpreting the information contained in insider trading.

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 insider 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 insider trades and didn't 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. 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 those 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 the absolute forecast error on the interaction between connect and analyst skill dummy and report the result in column (4) of table 6. As we can see, the coefficient on the connect dummy is one time larger when the analyst is less skilled compared to when the analyst has above median skill, 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 the connected analysts are able to get access to additional information contained in insider trading beyond what disclosed in public SEC filings. The information advantage comes from connected analysts' interaction with the trading desk person who executes insider's trades. To substantialize this assumption, we conduct a geography-based test. The idea is that analysts who are geographically close to the trading desk person should benefit more from the relationship between her brokerage firm and insiders. 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 insiders this information is available, and the broker assigned by the brokerage firm is almost always located close to the trading client. We regress forecast error on the interaction of connect dummy and same location dummy. The result is reported in column (5) of table 6. The coefficient on the connect dummy is -0.185 (t=-2.69) when the analyst and insider are from the same MSA area, while it is only -0.053 (t=-2.04) when they are not located in the same city. This supports our premise that geography proximity facilitates the information flow between the connected analyst and insider brokers.

3.3 Market reactions to connected analysts' recommendation changes

Given that connected analysts are more accurate, the natural question that arises is whether the market pays 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 insider having traded through the brokerage.

To test this we examine the cumulative abnormal return around analyst recommendation change for the sample of recommendation changes by the connected analysts when she is better informed. We take the market reaction to recommendation changes by other non-connected analysts in the same quarter as control. Even if there is a difference in the market reactions, this could arise due to the connected analyst being better than the others, and may not have to do with the market reacting more to their being informed. To take care of this, we consider the difference in the market reaction of the connected analyst in periods when she is not informed, relative to other analysts in that period. Finally we examine the difference-in-difference of the market reaction. The results are presented in Panel A of Table 7 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, there is not statistically significant difference in the aforementioned difference in market reactions across periods after an insider trade and others. This suggests that the market fails to recognize the periods when the connected analyst is especially well informed.

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 effect:

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

We get similar results as above using this specification, which are presented in the Appendix.

3.4 Predictability of earnings announcement returns following connected recommendation changes

A test of whether the market underreacts to the information contained in the connected analysts' recommendation, 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 higher signal-to-noise ratio. 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 8. For connected analysts 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. As seen in Table 8, in periods when the connected analyst is better informed, being below the consensus is associated with a 0.56% lower return around the next earnings announcements compared to being below the consensus 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.

3.5 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 the percentage absolute forecast error (PAFE) with the percentage signed 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. 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.

3.6 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, for two reasons. First, the consensus of 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 forecast (Bradshaw, Brown and Huang, 2013). Second, the information advantage that insider analysts 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 whether the information advantage enjoyed by inside analysts extend to their ability to make more accurate forecast on future stock price. 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 in report in table 9. We control for the same set of paired fixed effect and an affiliation dummy in the regression. We do not control for the forecast age because for target price forecast, the forecast age is always 12 month. 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 over the sample period of 1999 to 2013 is 52%[3], so connected analysts on average reduce forecast error on target price by 2% relative to mean. The result shows that although insider analysts' information advantage extend to more accurate target price forecast, economically it is much weaker compared to their forecast on firm earnings. This is consistent with our prior that the nature of the private information that insider analysts have access to is more related to earnings rather than stock price directly.

3.7 Long-horizon Earnings Forecast Accuracy

The information contained in insider trades could be either short lived or long lived. Our analysis so far mainly looks at whether inside analysts use the "soft" 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. Analyst also produce two-year ahead EPS forecast 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 long-term growth rate.

We control for the same set of paired fixed effects in long-horizon tests as we do for the 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 the analyst

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

issues an earnings forecast on a stock following the firm's insiders trade through the brokerage house employing this analyst. The result is reported in column 1 of Table 10. The coefficient on the connect dummy is -0.028 and significant at 10% level. The mean percentage absolute forecast error for FY2 EPS across our sample is 2.45%, so connected analysts on average have 1.14% 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 when 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. 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.[4] 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 10. The coefficient on the connect dummy is -0.52 and significant at 10%. The mean absolute forecast error on long-term growth rate (in percentage) in our sample is 19.47, so connected analysts on average have 2.67% smaller forecast error on long-term growth rate compared to the sample mean forecast error.

Overall, the results suggest that inside analysts' information advantage also extends to forecasting more accurate long-horizon earnings and earnings growth rate, but the effect is much smaller compared to short-horizon earnings forecast, both economically and statistically.

[4] 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.

3.8 Robustness Checks

In this section, we conduct more robustness tests on our baseline regression. The result is reported in table 11. We first winsorize our dependent variable, PAFE, at different threshold. 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. As we can see, the coefficient on the connect dummy is always significantly negative not matter what threshold we use to winsorize our dependent variable. In column (3) and (4), we use the stock price one month and one quarter prior to earnings announcement date to scale absolute forecast error, respectively. 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 connected analyst may not revise her earnings forecast when the "soft information" she get 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 addition control variables, forecast frequency and firm-specific relative experience, which have been shown by literature that 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 that of all other analysts who are currently following the same firm. As we can see from column (6), our result doesn't change with the two additional controls.

3.9 Falsification Tests of the Channel

Our results so far is consistent with the story that inside analysts get some 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 such as school ties between analyst and firm insiders unlikely to explain our finding. However, some more sophisticated version of direct connection between analyst and firm manager could potentially be consistent with our result. For example, Cohen, Frazzini and Malloy (2012) finds analysts who have attended the same college as the firm managers have information advantage on the connected firm when making recommendations. While the school ties between analyst and insider is always there, the information flow from insider to analyst is not constant. Insiders may have private information over the market in some periods, but not in all periods. If this is true, our result that inside analyst is more accurate only when firm insiders trade through the broker could be due to the fact that the occurrence of insider trades is correlated with the arrival of private information that flows from insider to analysts directly through school ties. In other words, the analyst*firm fixed effect doesn't fully rule out the school tie story because information flow attached to school ties is time-varying.

To substantialize that the channel that inside analyst get more accurate is indeed from the brokerage firm that insiders trade through, we conduct three fasciation tests. Specifically, we consider the break of the analyst-firm connection due to analysts changing job, insider changing broker and insider changing job. We then create a pseudo connect dummy between analyst and firm when the link is actually not there. We regress the percentage absolute forecast (PAFE) on the pseudo connect dummy and see whether we get the same result as we get for the true connect dummy.

Consider first that the analyst moves to a non-connected brokerage house but covers the same firm. We define a pseudo connect dummy equal to one when the analyst issues a new forecast within 1 year following the firm insiders trades through the old broker that the analyst no longer work there anymore. We then regress PAFE on this pseudo connect dummy, with and without the true connect dummy. The results are reported in column (1) and (2) of table 12. If the story is time-varying information flows attached to school ties between insiders and analysts, we should find the pseudo connect dummy to be significantly negative since changing to a non-connected broker shouldn't affect the school tie. On the contrary, the pseudo connect dummy should be insignificant if the channel is through the connected brokerage firm that we have in mind. 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.

Our second falsification test considers the case that the insider switches to a different broker to execute his trades. Similarly, we create a pseudo connect dummy equal to one when the analyst at the no-longer-connected brokerage issues an earnings forecast following the firm insider trades through the new broker. The result is reported in column (3) and (4) of table 12. The coefficient on the pseudo connect dummy is close to -0.003 and not significant. This result again rules out the time-varying school tie-based information flow story, but is consistent with the channel that we want to advocate in this paper. Our last falsification test consider the case that the insider moves to a new firm but keeps the same broker for executing his trades. Again we construct a pseudo connect dummy assuming the link between analyst and firm is still there (but actually not) when the insider at the new firm trades through the same broker. The result is reported in column (5) and (6) of table 12. The coefficient on the pseudo connect dummy in this case is positive and insignificant.

In summary, all three falsification tests reinforce the channel through which inside analysts have information advantage in their earnings forecast is from the brokerage firm that firm insider trades through, rather than direct connection between analysts and firm managers.

4. The inside broker's information advantage: channels

We gave an example in the introduction of 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 also might 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.

In sum, there are various clear reasons why one might expect the one other party directly involved in the insider trading process, 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 before – 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.

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?

4.1 A test of the channel

In general it is difficult to show definitive evidence of what the broker might know which is informative for the insider analyst but not for the rest of the market. 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 insider broker could have known it 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 plan of the insider 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 trades by an insider 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 and opportunistic trades following Cohen et al. (2013), i.e., insider trades which occur in the same calendar month for three consecutive years. We then define a dummy variable indicating whether the trades belong to a routine pattern or opportunistic pattern. Within all the routine trades, we further define three dummies referring to the first, second and third year (or beyond) trade in the whole sequence of routine insider trades. We then regress the percentage absolute forecast error (PAFE) on the interaction between these four dummies with the connect dummy. The result is reported in Table 13. For the routine trades, the magnitude on the connect dummy monotonically decreases from the first-year trade to the third-year trade. While the connect dummy 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 dummy following the first-year routine trade is even larger than that of the opportunistic trades, though statistically it is less significant because of the smaller sample size[5]. Since only the connected analysts likely know the trades belong to a regular trading pattern at the beginning of the 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 by connecting to the firm through brokerage that firm insiders trade through.

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

[5] 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.

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 India. By talking to the broker the analyst guesses, correctly, the company is likely to launch its products in India. 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 India. 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 doesn't 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 (possibly non-monetary) benefit.

From the perspective of making markets more efficient, it makes sense to give incentives to market participants to do their own research and uncover new information. From past legal cases it seems that the law recognizes does this need and tries to balance this aspect with trying to prevent insider trading. Especially in case of analysts, who usually make their information public, the phenomenon we document results in making the prices more efficient without leading to a pecuniary gain for a small set of people. Consequently, this is likely to be considered fine from a legal perspective. Nevertheless, our results point to an information advantage of the broker, and as discussed earlier, a possibility of other activities that will be considered illegal does remain, for example tipping clients selectively, which we do not explore in this paper.

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 parties involved. As part of such regulations, for example, insiders are required to disclose their precise trades. But does this disclosure contain all information relevant for the firm? In this paper, we argue that it is not.

We identify the stock broking house that firm insiders trade through, 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 forecasts in periods when the insider does not trade. The inside broker's information advantage is stronger for small, opaque firms on which other analysts disagree the most.

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 its private information on the nature of the trading instructions from their clients – and clients may not only mean firm insiders.

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.

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

SEC USE ONLY
DOCUMENT SEQUENCE NO.
CUSIP NUMBER
WORK LOCATION

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

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)

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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: 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 D: 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: 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 5: 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 6: 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 7: 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-control	pseudo connect	control	pseudo - 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-control	pseudo connect	control	pseudo - 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 8: 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 9: 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 10: 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 11: 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 12: 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 the firm insiders trades through the old broker that the analyst no longer work there anymore. In column (3) and (4), we consider that firm insiders change the broker but stays 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 firm insider trades through the new broker. In column (5) and (6), we consider that insiders moves to a new firm but keeps using the same broker. Specifically, we create a pseudo connect dummy equal to one when the analyst issues an earnings forecast (on the old firm) within 1 year following insiders at the new firm trades through the broker. 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 change broker, but stay at the same firm		Insider change job, but keeps the same broker	
	(1)	(2)	(3)	(4)	(5)	(6)
connect		-0.0674**		-0.0673**		-0.0676**
		(-2.56)		(-2.56)		(-2.57)
pesudo_connect	-0.0168	-0.0201	-0.0066	-0.0026	0.0119	0.0181
	(-0.37)	(-0.45)	(-0.22)	(-0.09)	(0.19)	(0.29)
fore_age	0.0509***	0.0506***	0.0509***	0.0506***	0.0509***	0.0507***
	(6.03)	(6.00)	(6.02)	(6.00)	(6.03)	(6.00)
affil	-0.1630	-0.1622	-0.1630	-0.1622	-0.1631	-0.1623
	(-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 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: 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 2: 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 3: 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