Inside Brokers: Internet Appendix

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1 Return Predictability of Form 144 Trades

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

2 Robustness of Analyst Forecast Tests

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

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

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

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

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

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

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

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

3 Robustness of Affiliated Fund Trading Results

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

4 Timing of Inside Broker-Affiliated Analysts' Forecast Revision

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

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

5 Cross-sectional Heterogeneity

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

5.1 Broker-Affiliated Analysts

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

5.1.1 Which Analysts?

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

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

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

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

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

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

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

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

5.1.2 Characteristics of insiders' firms and trades

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

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

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

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

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

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

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

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

5.2 Broker-Affiliated Mutual Funds

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

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

6 Pre-Regulation Fair Disclosure vs. More Recent Period

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

7 Legality: A discussion

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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Figure IA.1

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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)

Table IA.1: Sample Coverage of the Brokers

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

Panel A: Brokers used for analyst sample

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

Panel B: Brokers used for mutual fund sample

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

Table IA.2: Return Predictability of Form 144 Trades

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

Panel A: Full sample calendar-time portfolio

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

Panel B: Fama-MacBeth Regression

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

Table IA.3: Robustness of Analyst Forecast Tests

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

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

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

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

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

Table IA.5: Forecast Accuracy vs. Optimism

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Panel B: Characteristics of insiders' firms and trades

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

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

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

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

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

Panel B: Characteristics of insiders' firms and trades

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

Table IA.12: Before and After Regulation Fair Disclosure

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

Panel A: Broker-affiliated Analyst Forecast Accuracy

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

Panel B: Profitability of Broker-affiliated Fund Trades

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