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ABSTRACT

We study trading patterns of corporate insiders in their own personal portfolios. To do so, we identify accounts of corporate insiders in a large dataset provided by a retail discount broker. We show that insiders overweight firms from their own industry. Furthermore, insiders earn substantial abnormal returns only on stocks from their industry, especially obscure stocks (small, low analyst coverage, high volatility). In a battery of tests, we find no evidence that corporate insiders use private information and conclude that insiders have an informational advantage in trading stocks from their own industry over outsiders to the industry.

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1 Introduction

A vast literature examines the ability of individuals to trade profitably.[1] Although most analyses find that individuals lose on average from trading (e.g., Barber and Odean, 2000), a few studies show that some individuals consistently outperform the benchmarks (e.g., Seru, Shumway, and Stoffman, 2010). One potential source of trading advantage for some individuals is familiarity with the stocks and industries they trade, i.e., having better tools to decipher public information. Several studies attempt to examine this source, yet the results are mixed. In the context of retail traders, Døskeland and Hvide (2011) document that individuals overweight stocks of companies in their employment industry, but they find that they earn negative returns. The authors attribute this result to overconfidence. In the context of mutual fund managers, Pool, Stoffman, and Yonker (2012) find that managers overweight stocks from their home states but do not exhibit superior performance. Kacperczyk, Sialm, and Zheng (2005) show that mutual fund managers who have concentrated positions in a few industries achieve positive abnormal returns. Kempf, Manconi, and Spalt (2014) report that mutual fund managers outperform in industries in which they have more investing experience. Finally, Cici, Gehde-Trapp, Göricke, and Kempf (2014) find that mutual fund managers do not overweight industries in which they previously worked. However, stocks that they pick from these industries outperform stocks in the rest of their portfolio. Given the mixed results, it is important to understand whether familiarity with the industry is related to skill.

In this paper, we provide evidence on the topic from a novel source. We examine trades made by corporate insiders in their own personal portfolios. In this setting, top corporate executives serve as retail traders. However, compared with the average employee (studied in Døskeland and Hvide, 2011), our executives have a better understanding of their industry. We contrast their trading patterns and performance in stocks that belong to their industry and those outside the industry.

Our study also contributes to our understanding of the trading and portfolio holdings of corporate executives. Past research has shown that insiders can trade profitability on their own firm stocks: Seyhun (1998), Lakonishok and Lee (2001), Cohen, Malloy, and Pomorski (2012), and Ben-David and Roulstone (2012) report that prices drift for up to a year following insider

[1] See Barber and Odean (2011) for a comprehensive review of the findings of the individual investors literature.

purchases. This performance is often ascribed to private information that insiders hold (e.g., Seyhun, 1998). However, little is known about the composition of insiders' full portfolios or the trades they make outside their own firm. Because our data cover all stocks that insiders trade with the retail broker, we can provide the first insight into the portfolio composition and diversification choices of insiders.

Our data come from matching a transaction-level retail trading database (used in Barber and Odean, 2000) with insider transactions as reported in U.S. Securities and Exchange Commission (SEC) records. Matching these databases allows us to identify insiders in the retail database and track their other, non-own-firm, trades.

We start by examining the trade composition of insiders. We first look at whether insiders hedge their human capital by underweighting stocks in their industry of profession. In contrast, our results show that insiders actually overweight their portfolios with stocks in their own industry. We estimate that 8.4% of their trades are in own-industry stocks, even though own-industry firms comprise only 4.1% of the total market capitalization, on average.

Next, we test whether insiders exhibit skill with respect to their stock buy-and-sell decisions. Also, we explore whether this outperformance is reflected in all stock picks or is confined to trades in which insiders have professional expertise. We find evidence that insiders exhibit skill only in their own-industry trades. Given that own-industry stock returns are likely highly correlated with returns on insider human capital, insiders should only overweight their portfolios in own-industry stocks if they possess some advantage in trading these specific stocks. Indeed, we find evidence that insiders make large abnormal returns on their own-industry trades, both purchases and sales, but exhibit no outperformance in non-own-industry trades. These results are robust to the use of holdings-based calendar-time portfolios, transactions-based calendar-time portfolios, and buy-and-hold abnormal returns.

The difference in the performance between own-industry and non-own-industry trades of insiders is stark. A portfolio of own-industry buys minus own-industry sales earns a Carhart alpha of 16% per year. In contrast, a portfolio of non-own-industry buys minus non-own-industry sales earns a statistically insignificant alpha of 3% per year.

We also find that insider outperformance in own-industry stocks does not merely stem from an ability to time industry returns. Rather, insiders exhibit within-industry stock-picking ability:

stock buys within industry outperform other stocks in the same industry, and stock sells within industry underperform other stocks in the same industry. That is, insiders are able to identify winners and losers in the cross-section of industry stocks.

We consider two main hypotheses for the source of superior performance of corporate insiders in expertise stocks. The first is that insiders are better at deciphering public industry information ("public information hypothesis"). The second is that insiders use some internal information either about their industry peers or from their own firm to trade other firms ("private information hypothesis"). Given the potential legal ramifications of insider trading, trading other stocks might be a safe way to exploit private information. For example, an insider may trade stocks of customers, suppliers, or competitors. The two hypotheses are, of course, not mutually exclusive. It is possible that the abnormal returns that insiders earn on their expertise trades are attributable to a combination of skill at deciphering public industry information and access to private information.

Our tests find evidence only in favor of the public information hypothesis. We document that the superior performance of the insiders in expertise stocks is concentrated in obscure stocks: small stocks, stocks with low analyst coverage, and those with high idiosyncratic risk. This result is consistent with insiders having the skill to better process information than other market participants.

We conduct four tests to explore the possibility that insiders use private information when trading own-industry stocks but find little evidence to support this effect. First, we examine the trades of insiders who work for financial firms (about 20% of insiders). Executives in financial firms have information on other firms from other industries, and a growing recent literature shows that financial institutions exploit this private knowledge of other firms for trading purposes.[2] However, we do not find that financial firm insiders exhibit superior trading in non-financial stocks. Second, we examine whether insiders trade ahead of merger and acquisition (M&As) announcements. To identify the presence of trading on private information, prior studies have primarily focused on trading activity in the period leading up to an M&A announcement (e.g., Keown and Pinkerton, 1981; Cao, Chen, and Griffin, 2005; Bodnaruk, Massa, and Siminov, 2009;

[2] Recent papers documenting evidence of informed trading by financial insiders include Acharya and Johnson, 2007; Massa and Rehman, 2008; Bodnaruk, Massa, and Siminov, 2009; Acharya and Johnson, 2010; Ivashina and Sun, 2011; and Massoud, Nandy, Saunders, and Song, 2011.

Griffin, Shu, and Topaloglu, 2012; Kedia and Zhou, 2014; Augustin, Brenner, and Subrahmanyam, 2015). We find no evidence that insiders trade ahead of M&A activity, again contrary to the private information explanation. Third, we also find nothing to suggest that these insiders trade closely related stocks as a means to profit from own-firm private information, as within-industry trades do not predict the earnings surprises of insiders' own firms. Fourth, we find no evidence that own-industry trades in a given firm are correlated with insider trading in that firm. In short, we find no smoking gun for the use of private information.

Thus, the interpretation most consistent with our findings is that industry expertise drives the superior returns of insider trading in peer firms. Specifically, insiders are better able to decipher public information about firms in their own industry. It is important to note that while definitively excluding the possibility that insiders are trading on private information is impossible—as the motivation behind insiders' trades is not directly observable—our results appear to provide little support for this source of profits.

Our finding that industry experience provides an increased ability to decipher public information within the industry of expertise is consistent with evidence in the recent literature. Alldredge and Cicero (2015) show that insiders often rely on public information when making profitable sales of own-firm stock. Bradley, Gokkaya, and Liu (2015) determine that analyst forecasts are more accurate for firms residing in industries in which the analyst has previous work experience. In the mutual fund setting, Cici, Gehde-Trapp, Goricke, and Kempf (2014) find evidence that mutual fund managers' trades in industries in which the manager has previous work experience outperform other trades.

2 Data and Summary Statistics

2.1 Corporate Insiders Sample

Our data come from two matched datasets. The first contains the trading records of 78,000 individual investors at a large discount broker (henceforth, the LDB dataset) from January 1991 to November 1996. These data were previously analyzed by Barber and Odean (2000). The second dataset is the activity of all corporate insiders, who are required by law to report their trading activity in their own firm to the U.S. Securities and Exchange Commission (SEC). We compile this database from the insider trading files from the National Archives.

By matching individual trades in these two databases, we identify 105 LDB accounts that belong to insiders of publicly traded firms. The matching procedure of the two databases is done in three main steps. First, we match individual trades executed at the LDB with those filed with the SEC. Second, we consider all potential LDB account–corporate insider pairs at the account level and assign each a matching-likelihood score. Finally, we confirm the matches by manually inspecting the LDB trades and the SEC filings. The Appendix includes an in-depth description of the matching procedure.

2.2 Other Sources of Data

Our analysis includes all trades of at least $100 in common shares (share code 10 or 11) of AMEX, NASDAQ, and NYSE firms that have a valid four-digit SIC code, a 49 Fama-French industry assignment, and a DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997) assignment. We aggregate trades daily; in other words, within each day we treat multiple trades in the same stock by the same individual as a single net trade. We drop observations for which the net traded quantity in a day is zero.

We use a variety of data sources to study the performance of the corporate insiders' trades. For purposes of comparison, in some tables and figures we display statistics regarding the trades of the other retail investors in the LDB database. We obtain stock returns, market capitalization, and Fama-French (1993) factor data from the daily and monthly CRSP files, and accounting data from Compustat. We pull earnings announcement data, including the number of analysts covering each stock, from I.B.E.S. We obtain returns and stock assignments to the DGTW characteristics-based benchmarks from Russ Wermers' website, and use these assignments to calculate the daily version of the DGTW benchmark returns used in the analysis.[3]

Throughout the paper, we use the 49 Fama-French industry portfolios as industry benchmarks. Stock assignments to the 49 Fama-French industry benchmarks and their daily and

[3] The DGTW benchmarks are available on http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

monthly returns are downloaded from Kenneth French's website.[4] The Fama-French industry classifications are sufficiently close to the three-digit SIC code industry definition we employ to define expertise trades (trades of firms within the insider's same industry, see Section 2.4 for further discussion) and at the same time they avoid classifying very small groups of stocks as stand-alone industries; hence, the 49 Fama-French industry returns are less susceptible to extreme idiosyncratic returns than the three-digit SIC code returns. Our results are, however, robust to the choice of the industry benchmark.

2.3 Summary Statistics

Table 1 presents summary statistics for the insiders in our sample. The 105 insiders are affiliated with a total of 171 companies, and made 5,459 trades. On average, each insider is affiliated with 1.63 companies, and the median insider is affiliated with only one firm. In our sample, the maximum number of companies an insider is affiliated with is seven. The fifth row of Panel A shows that insiders' companies are similar in size to the average firm listed on NYSE and AMEX, as the average insider firm is in the 48th percentile of the size distribution of NYSE-AMEX companies. We also report details regarding the industry composition of insiders in our sample. Financials are the most heavily represented industry in our sample, with 14.6% insiders associated with firms in this industry, followed by computer hardware (7.6%) and business services (5.3%). We verify in later analyses that our results are robust to excluding financial industry insiders.

2.4 Defining Expertise Stocks

We define "expertise trades" in reference to an insider's firm. Stock trades made within the same three-digit SIC industry of the insider's firm are considered expertise trades, and all trades outside of the insider's industry are defined as "non-expertise trades." Panel B of Table 1 displays the characteristics of insiders' trades. In our sample, insiders have nearly twice as many trades in own-firm stock as they do in the stocks of other firms in the same industry, and they have about ten times as many non-expertise trades as they have expertise trades. The average dollar value per trade is larger for expertise trades than for non-expertise trades ($27,656 vs. $20,979), and larger

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

for expertise trades than for the average retail trade ($27,656 vs. $13,174), but is smaller than the average value of own-firm open-market trades ($61,374). Finally, Panel C shows that relative to non-expertise purchases and the purchases of all other retail traders, the expertise stocks purchased are less likely to be low book-to-market (B/M) stocks, and are slightly more likely to be stocks with high past returns. However, in general, expertise purchases are quite similar to the non-expertise stocks and retail stocks purchased along the dimensions of size, book to market, and past returns.

3 Overweighting Expertise Stocks

We first examine the insiders' trade composition. Because the value of insiders' human capital is correlated with the stock price performance of own-firm stock as well as own-industry stocks, insiders should underweight stock holdings from their own industry unless they have an informational advantage or suffer from a familiarity bias (Pool, Stoffman, and Yonker, 2012; Døskeland and Hvide, 2011).

Table 2 examines the proportion of expertise trades of insiders relative to various benchmarks. Panel A gives equal weight to all trades made by insiders, and compares the actual percentage of expertise trades made by insiders to the percentage an insider would be expected to make if she exhibited no trading tilt toward her own industry. The first two columns show that 8.39% of all trades made by insiders are classified as expertise trades. This is a substantially greater tilt toward expertise trades than one would expect unconditionally, as Column (1) shows that the expected percentage of expertise trades should only be 4.09% based on the number of expertise stocks relative to the universe of stocks in NYSE, AMEX, and NASDAQ. In other words, if insiders equally weighted all stocks, they would trade expertise stocks with only about half the frequency with which they are traded in our sample.

One concern with the results in Column (1) is the possibility that the insiders' industries in our sample are weighted toward industries in which retail traders particularly like to trade. If this is the case, then insiders' inclination toward expertise trades may not differ from the norm, defined as the frequency with which retail traders in aggregate trade in this industry. Column (2) shows that not only do insiders trade expertise stocks with a greater frequency than they should based on the percentage of own-industry stocks in the market portfolio, but they also trade own-industry stocks with a far greater frequency than other retail traders trade stocks in that given industry. In Column (2), the benchmark is the observed percentage of trades in that industry for all other (non-insider) retail traders in the LDB. The third row, showing actual minus benchmark, compares the actual percentage of insider trades in expertise stocks with the frequency with which all traders in the database trade stocks in that industry. Trades in expertise industries comprise only 4.23% percent of the trades of other retail traders (in line with the benchmark of 4.09% in Column (1)), which is again substantially lower than the frequency exhibited by insiders. The last row of Panel A shows that by this definition, insiders trade expertise stocks 1.99 times more than expected.

The analysis in the first two columns pools the trades of all insiders together and gives each trade equal weight. By construction, this methodology gives more weight to the trades of insiders who trade more frequently. In the last two columns of Panel A, we instead calculate the trading tilt weighting each trader equally. Our conclusion that insiders overweight expertise stocks continues to hold and is in fact even stronger when calculating averages over traders rather than over trades.

Panel B shows that the overweighting of expertise trades by insiders is even greater if we use a dollar-weighted trade volume definition. In this case, the first two columns show that insiders trade expertise stocks 2.72 times more than expected when using the benchmark of NYSE, AMEX, and NASDAQ stocks, and 2.26 times more than expected when using the trades of other retail traders as a benchmark. Columns (3) and (4) again demonstrate that the discrepancy between expected (benchmark) and actual expertise trades is even larger when using a methodology that averages over traders rather than trades.

In summary, the results clearly show that insiders overweight trades in their own-industry stocks. The substantial overweighting is not due to insiders' industries being skewed toward those in which retail traders trade disproportionately, as we also show that insider trades in these industries are overweighted relative to the trades of other retail traders in these same industries. We next examine whether overtrading in expertise industries reflects a familiarity bias, or whether insiders possess greater expertise in trading own-industry stocks.

4 Trade Performance

4.1 Returns of Expertise Trades

We next look at the profitability of insiders' expertise and non-expertise trades. Two potential hypotheses could explain the propensity of insiders to overweight trades of own-industry stocks. First, the familiarity bias hypothesis predicts that insiders tilt their trading toward own-industry stocks because they are more familiar with or aware of these stocks. For example, Pool, Stoffman, and Yonker (2012) find that mutual fund managers overweight stocks from their home states even though own-state holdings do not perform better than other holdings. Similarly, Døskeland and Hvide (2011) document that retail traders in Norway overweight industries in which they are employed, with no excess performance.

Second, the informational advantage hypothesis predicts that insiders tilt their trading toward own-industry stocks because they possess an advantage in trading these stocks due to, for instance, an increased ability to decipher public information. By exploring the returns to insiders' trades we can discriminate between these two hypotheses. The familiarity bias motive for trading predicts that own-industry trades should not exhibit outperformance, whereas the informational advantage hypothesis predicts that own-industry trades should outperform.

Figures 1 and 2 preview our main results. We begin by plotting the event-time buy-and-hold DGTW-adjusted returns for portfolios mimicking the purchases of corporate insiders and other retail traders in the LDB database for 63 trading days after portfolio formation. We follow Seasholes and Zhu (2010) and skip a day between the transaction and the date at which we add the stock to our portfolio. Figure 1 plots DGTW-adjusted cumulative returns for insiders' expertise buys, for insiders' non-expertise buys, and for buys of all other traders in the LDB database that we study. The figure shows that insider expertise buys perform extremely well in the period following purchase, while non-expertise buys and the buys of all other traders earn returns that are negative or near zero. Figure 2 shows returns for long buys and short sells; again, expertise trades perform substantially better than non-expertise trades and the trades of all other traders. Although this evidence shows that expertise buys substantially outperform expertise sells, non-expertise buys do not outperform non-expertise sells, nor do the buys of all other traders outperform the sells of these traders.

4.1.1 Holdings-Based Calendar-Time Portfolios

Our main analysis uses calendar-time portfolios to assess the profitability of insiders' trades. Fama (1998) and Mitchell and Stafford (2000) strongly advocate the use of the calendar-time portfolio methodology, and Seasholes and Zhu (2010) further argue that the calendar-time portfolio methodology addresses a number of pitfalls that can potentially affect studies of retail traders' investments.

We begin by using the calendar-time portfolio methodology to assess the holdings-based returns of insiders. This analysis holds stocks for the period in which they are in an investors' portfolio, and drops stocks from the portfolio at the end of the day on which they are sold. We also use a transactions-based calendar-time portfolio methodology to assess whether the expertise stocks that insiders buy outperform the expertise stocks that insiders sell. The transactions-based methodology holds purchased or sold stocks for a fixed period of time after the transaction. We also show that our results are robust to using the buy-and-hold abnormal return methodology (BHAR) of Barber and Lyon (1997).

Table 3 presents the main results using the holdings-based methodology. To avoid mean-reversion induced by the bid-ask spread, we follow Seasholes and Zhu (2010) and skip a day between the actual purchase date and when we add the stock to our portfolio. Stocks are dropped from the portfolio at the end of the day on which they are sold by the investor. Appendix B provides a detailed explanation of the holdings-based calendar-time methodology. Panel A of Table 3 shows raw portfolio returns by sample year, reported in daily basis points, for all retail traders, all trades of insiders, expertise trades of insiders, and non-expertise trades of insiders. Panel B presents Fama-French alphas (Fama and French, 1993), Carhart alphas (Carhart, 1997), HXZ Q-factor alphas (Hou, Xue, and Zhang, 2015), and Fama-French five-factor alphas (Fama and French, 2015). The results are consistent across all models. Column (2) of Panel B shows that, in general, insiders do not exhibit skill, as their trades earn an insignificantly positive alpha of around 1 basis point per day. However, consistent with insiders possessing skill in trading in their own industry, Column (3) shows that insiders do outperform on their expertise trades. Expertise trades make a statistically significant alpha of between 4.9 and 5.8 basis points per day, depending on the model used. In contrast, the non-expertise portfolio of insiders produces a small, statistically insignificant positive alpha. For comparison purposes, Column (1) reports the alpha for the portfolio of all other retail traders. Consistent with past research, retail traders do not exhibit skill on average.

In the Internet Appendix, we show that the results are robust to a variety of sample choices. One concern is that there are fewer stocks in the portfolio at the beginning of the sample. Table A2, Panel A shows that excluding 1991 from the analysis does not change the results. Table A2 further addresses the concern that there are unequal numbers of stocks in the portfolio across different days. Table A2, Panel B weights each day by the aggregate dollar value invested in the portfolio on a given day. Table A2, Panel C weights each day by the number of stocks in the portfolio. Both alternative weighting methodologies deliver the same results: the expertise portfolio exhibits statistically significant outperformance, while the non-expertise portfolio generally fails to exhibit skill. A final concern is that microcap stocks might be disproportionately influencing the results. Table A2, Panel D shows that excluding microcaps from the analysis results in large, statistically significant alphas for the expertise portfolio but not for the non-expertise portfolio.

4.1.2 Transactions-Based Calendar-Time Portfolios

Next, we use a transactions-based calendar-time portfolio methodology to assess whether insiders exhibit skill in their own-industry trades. If insiders have value-relevant information regarding stocks in their industry of employment, then a portfolio of expertise stocks purchased by insiders should outperform a portfolio composed of the expertise stocks sold by insiders. The average holding period for insiders in our sample is roughly one year. We therefore examine portfolios that hold stocks for 12 months following a buy or sell transaction. In the Internet Appendix we show that all of the results are robust to a three-month or six-month holding period. Appendix C gives further details about the transactions-based methodology.

Table 4 separately reports the returns to buy and sell portfolios for expertise trades, non-expertise trades, and the trades of all other retail traders. Columns (1) and (2) show that expertise buys outperform expertise sells by over six basis points per day. In contrast, the non-expertise buys of insiders outperform non-expertise sells by less than one basis point per day, while buys actually underperform sells for all other retail traders. The next four columns analyze the annual differences in the buy and sell portfolios. Columns (3) and (4) present evidence that expertise buys outperform expertise sells by a statistically significant 15.1% per year, and Columns (5) and (6) show that the expertise buy-minus-sell portfolio has a statistically significant Carhart alpha of 16% per year. Consistent with the earlier holdings-based results, non-expertise trades of insiders do not exhibit any skill, as the buy-minus-sell portfolio earns only a statistically insignificant alpha of 3% per year. Panel B shows that the results from equal-weighted portfolios are similar to the value-weighted results reported in Panel A. Table A3 of the Internet Appendix presents a number of robustness tests that confirm that the results are robust to weighting days by aggregate dollar value invested, and that the results are robust to the exclusion of microcap stocks and to the use of three- and six-month holding periods.

4.1.3 Buy-and-Hold Abnormal Returns

For robustness, we next report buy-and-hold abnormal returns and trade-size-weighted buy-and-hold abnormal returns. The transactions-based calendar-time portfolio methodology does not facilitate the examination of short-horizon windows, as for instance, a three-month calendar-time portfolio will at times have very few stocks in the expertise portfolio. Buy-and-hold portfolios do not have this drawback. To gain further insight into the shorter-term performance of the stocks purchased and sold by insiders, our buy-and-hold analysis focuses on three-month horizons. The Internet Appendix reports results for 12-month horizons for all of our tests.

Table 5 examines the performance of expertise trades, non-expertise trades, and the trades of all other retail traders using the buy-and-hold methodology. Columns (1) and (2) confirm the calendar-time portfolio methodology results. Column (1) shows that expertise buys outperform expertise sells by 5.96% in the three months after expertise trades. On the other hand, non-expertise buys actually underperform non-expertise sells by a statistically significant 1.2%. The DGTW-adjusted results reported in Column (2) lead to the same conclusion: expertise buys earn significantly higher returns than expertise sells, but the same is not true of non-expertise trades. The results again support the conclusion that insiders' own-industry trades exhibit skill, while their trades outside their industry of knowledge do not.

The last three columns report trade-size weighted returns. Trade size appears to be correlated with performance. The outperformance of expertise buys relative to sells is substantially higher when trade-size weighting the returns. This is consistent with evidence from the mutual fund literature that stocks overweighted by a mutual fund or fund family tend to outperform in the future, presumably because they reflect the “best idea” trades of a fund or family (Pomorski, 2009; Cohen, Polk, and Silli, 2010). The results we present in the rest of the paper are calculated weighting each trade equally; however, the same results hold, and are often stronger, when we weight each trade by its size. We choose to present the more conservative equal-weighted for one primary reason: because we only observe the insiders’ stock trades with the LBD trading account, we cannot estimate each insider’s overall wealth and therefore cannot disentangle a conviction effect from a wealth effect. In other words, we cannot completely rule out the possibility that larger trades have high returns because, at least in part, wealthier insiders are more skilled rather than because insiders overweight stocks for which they hold stronger conviction.

In some cases, trades are closed out before the end of the three-month period, and these sale decisions are not reflected in the returns reported in Table 5. Table A1 reports round-trip buy-and-hold abnormal returns that take into account the timing of the investor’s sale decision. The table separates trades into those held for less than three months and those held longer than three months. If a stock is sold before the end of the three-month holding period, then the three-month return is replaced with the holding period return.[5] As Table A1 shows, the results are robust to an analysis that takes into account the holding period of the insider, and accounts for these relatively shorter round-trip trades.[6]

Figure 3 provides information about the evolution of returns over the holding period. It shows a detailed buy-side analysis that takes into account the timing of the sale decision. The figure presents a daily analysis of the cumulative improvement of the buy-side portfolio results if we use a strategy that drops a stock from the buy portfolio at the end of the day on which is sold. Note that this will only have an effect on the results for stock purchases for which a sale occurs within the period of analysis, and the impact on the portfolio returns will be more important as

[5] In Table A1 and Figures 3a and 3b, we assume that the first sale following a purchase of the same stock by the same individual closes the individual’s position.

[6] Interestingly, when comparing the last row of the second and third set of results, we find that non-expertise and retail trades appear to exhibit the disposition effect in that the positions sold off early exhibit larger gains than the positions they continue holding. In contrast, expertise trades of insiders do not appear to exhibit the disposition effect, as the positions closed early exhibit smaller gains than those that they continue holding. The evidence is suggestive of skill ameliorating the bias of the disposition effect.

more time passes and more stocks are sold; for this reason, in this figure we extend the window of analysis from three months to 100 trading days.

Figure 3a shows the cumulative proportion of trades closed within a given number of trading days for the trades of insiders and all other traders. The figure indicates that insiders close positions of expertise trades more quickly than they do their non-expertise trades. For instance, about 30% of expertise trades have been closed within 30 trading days of a purchase, but only about 20% of non-expertise trades have been closed within 30 trading days of a purchase. While expertise trades close at a higher rate, non-expertise trades close at a rate similar to that of the average trade by all other traders.

Figure 3b shows the gain or loss that accrues as a result of the timing of sales. The figure displays the difference in return between the expertise buy portfolio that disregards the sale decision (buy-hold) and the expertise buy portfolio that takes into account the timing of the insider sale decision (buy-hold-drop). Specifically, if a stock is dropped during the analysis window, then the buy-hold-drop portfolio only holds the stock in the portfolio until the sale date of the insider, but the buy-hold portfolio holds the stock regardless of whether it is dropped before trading day *t*. As the insiders' expertise line indicates, the returns to the expertise buy portfolio substantially increase when the date of the insider sale is taken into account. On the other hand, the timing of sales does not seem to benefit insiders for their non-expertise purchases, as the dashed line indicates that the buy-hold-drop portfolio return is almost identical to the buy-hold portfolio return. The same is true for the trades of all other traders. Consistent with the earlier sales timing results, Figure 3b shows that substantial skill is exhibited in the timing of sales for expertise buys. On the other hand, we find no evidence of skill in timing of non-expertise buys or for the buys of all other traders. Overall, the results are consistent with insiders possessing the ability to identify winners and losers only in their own-industry trades.

The results in Figure 3 should be interpreted in light of prior studies' findings that retail investors who trade frequently do not outperform others (e.g., Barber and Odean, 2000) and that the stocks they trade perform better after they are sold than after they are bought (Odean, 1999). Figure 3 demonstrates that, in stark contrast with other retail traders, the performance of the insiders' expertise portfolios benefit substantially from the fact that insiders tend to trade frequently and to close their positions rapidly.

4.2 Industry Timing versus Stock Picking

The superior performance of expertise trades is potentially due to insiders' ability to time their own industries. We test this hypothesis by examining industry-adjusted excess returns. If the outperformance of expertise trades results from industry timing ability, then we would not expect to see outperformance when adjusting by industry returns. Industry-adjusted returns are presented in Columns (3) and (6) of Table 5. Buy-minus-sell expertise returns are similar and slightly smaller in magnitude than the DGTW-adjusted returns reported in the same table, indicating that insiders may possess substantial stock-picking skill that is not attributable to industry timing. The results suggest that insiders possess skill in identifying winners and losers in the cross-section of industry stocks.

We provide further evidence in Figure 4 that insiders' expertise trades reflect informed trading, as a sizable part of the returns to expertise trades are realized at the earnings announcements immediately following trading. Specifically, Figure 4 displays the subsequent earnings announcement for expertise and non-expertise trade stocks, conditional on the earnings announcement occurring within one quarter of the trade date. For instance, from the day before the earnings announcement ($t - 1$) to the day after the earnings announcement ($t + 1$), expertise buys on average experience abnormal returns of over 100 basis points, while expertise sells experience abnormal returns of over negative 100 basis points in the three days around their subsequent earnings announcement. Figure 4 further shows that a substantial part of the performance difference between expertise buys and non-expertise buys is realized around the first earnings announcement following the transactions. For comparison purposes, we also plot the average cumulative abnormal return (CAR) for all the other earnings announcements made by firms whose stocks are traded by the insiders but that are not preceded by an insider's trade. (We use the market value-weighted return as the benchmark.) These announcements are, on average, accompanied by slightly positive CARs, but the average t –1 to t + 1 CAR after expertise buys is about three times larger. The results provide strong evidence in support of the informational advantage hypothesis.

4.3 Local Expertise Stocks

Prior research indicates that investors outperform in their local stock picks (e.g., Coval and Moskowitz, 2001; Ivkovic and Weisbenner, 2005). If firms in an industry tend to cluster geographically, then expertise trades could be disproportionately tilted toward local stocks. We next examine whether the outperformance that we observe in expertise trades can be attributed to local firms.

We follow Ivkovic and Weisbenner (2005) and consider stocks of firms located within 250 miles of the insider to be local. Because the LDB database only contains zip code information for about 60% of the insiders in our sample, we use the zip code of the insider firm headquarters to define local stocks.

Table A5 of the Internet Appendix presents the results of this analysis. Ivkovic and Weisbenner (2005) report that 30% of retail investors' holdings are in local stocks. Table A5 shows that the corresponding number for insiders in our sample is about 25%, suggesting that, in general, insiders are slightly less prone than common retail investors to hold geographically close stocks. However, 43.4% of expertise trades are in local stocks, consistent with geographic clustering of industries. Panel A reports equal-weighted abnormal returns separately for local and nonlocal firms. Panel B presents a similar analysis on a trade-size-weighted basis. Both panels show that when focusing only on nonlocal stocks, expertise trades continue to exhibit substantial outperformance. The analysis clearly shows that the subset of expertise trades that are local are not driving the results.

Finally, we also assess the geographic distribution of insiders. Insiders in our sample are relatively dispersed, representing 40 different states, with the greatest number of insiders from California. In unreported analyses, we confirm that the results are robust to the exclusion of trades in firms headquartered in California.

5 Public versus Private Information

The abnormal returns for within-industry trades of insiders that we document in Section 4.1 are consistent with two potential explanations. The first is that insiders are simply better able to decipher public information about their industry of expertise ("public information hypothesis"). Recent evidence indicates that some individuals possess an advantage at interpreting public information in certain settings. For example, Alldredge and Cicero (2015) attribute some profitable insider trading to the ability of insiders to better interpret public information. Ivkovic, Sialm, and

Weisbenner (2008) show that individuals with more concentrated holdings outperform. Kacperczyk, Sialm, and Zheng (2005), Kempf, Manconi, and Spalt (2014), and Cici, Gehde-Trapp, Goricke, and Kempf (2014) all determine that some traders possess expertise in certain industries. Bradley, Gokkaya, and Liu (2015) also provide evidence that past industry experience is advantageous in deciphering public information, finding that analyst forecasts are more accurate for firms in industries in which the analyst has previous work experience. It is not surprising that insiders possess an advantage in trading on public information within their industry of expertise. The nature of insiders' jobs encourages them to be attentive to industry news and day-to-day developments.

A second possible explanation for abnormal expertise trades could be that insiders are trading on private information ("private information hypothesis"). If this were the case, expertise trades are profitable, not because insiders possess skill or expertise in deciphering public information, but rather because insiders are privy to private information regarding firms in their industry, and they use this information to make profitable trades.

5.1 Tests for Public Information

5.1.1 Hard-to-Value Stocks

If insiders possess an advantage in processing information within their industry of expertise, this advantage should be most valuable in the subset of stocks that is most difficult to value. We use three separate measures to characterize hard-to-value stocks, and each suggests that expertise trades are most profitable when concentrated in hard-to-value stocks.

To test the public information hypothesis, we use size, residual analyst coverage, and idiosyncratic volatility as proxies for hard-to-value. Hong, Lim, and Stein (2000) and Zhang (2006) argue that small stocks and stocks with low analyst coverage have more valuation uncertainty, while Zhang (2006) and Kumar (2009) maintain that stocks with higher idiosyncratic volatility also face greater valuation uncertainty. We follow Hong, Lim, and Stein (2000) and obtain residual analyst coverage from a regression of analyst coverage on size and a NASDAQ dummy. The regression is run each month in separate NYSE-AMEX size quintiles. We follow Ang, Hodrick, Xing, and Zhang (2006) and calculate idiosyncratic volatility using daily returns in month $t - 1$.

Table 6 presents the results of this analysis. Panel A classifies stocks by size, Panel B classifies stocks based on the residual analyst coverage measure of Hong, Lim, and Stein (2000), and Panel C displays results for stocks classified based on idiosyncratic volatility. Each panel displays future returns for expertise buys and sells of stocks that are split into two groups based on whether they are above or below the in-sample median for the given characteristic. In each of the three panels, the expertise buy minus expertise sell portfolio exhibits statistically significant differences in future returns for only the hard-to-value stocks.

In Panel A, expertise buys of hard-to-value stocks (stocks with below-median size) earn three-month future DGTW-adjusted returns that are 12.82% higher than for expertise sells of hard-to-value stocks. The difference is statistically significant. In contrast, expertise buys actually slightly underperform expertise sells (by a statistically insignificant -1.15%) for stocks of above-median size. Panels B and C provide very similar results when classifying stocks based on the characteristics of residual analyst coverage and idiosyncratic volatility. Regardless of the proxy for hard-to-value used, statistically significant outperformance of expertise buys relative to expertise sells is confined to only hard-to-value stocks. In Panel B, stocks with below-median residual analyst coverage exhibit a three-month future return differential of 8.51% between expertise buys and sells, while for those stocks with above-median analyst coverage, expertise buys earn a statistically insignificant 3.2% higher return than expertise sells in the three months following the transaction. The results are similar in Panel C, as the outperformance is again confined to only hard-to-value stocks. Within transactions for stocks with above-median idiosyncratic volatility, expertise buys outperform expertise sells by 10.74% over the following three months, while the difference is a statistically insignificant 1.06% for those stocks with below-median idiosyncratic volatility. The results are consistent with the hypothesis that insiders possess an advantage in deciphering information for expertise stocks—particularly among stocks that are the most difficult to value.

5.2 Tests for Private Information

We conduct several tests of the private information hypothesis. In the first two tests, we explore subpopulations of insiders to see whether they are more likely to exploit their internal information. Then, we examine whether the timing of expertise trades by corporate insiders coincides with M&A activity, with own-firm earnings announcement dates, or with the trades of insiders in the expertise firms. In all of these cases, insiders may be able to use private information when trading expertise stocks.

5.2.1 Insiders in Financial Firms

We examine whether a subset of the traders most likely to possess superior information—financial firm insiders—are disproportionately driving our findings. Of the 105 insiders in our sample, 23 are in financial firms. These financial firm insiders might have an informational advantage over insiders in other firms because they have access to their clients' non-public financial information, which they may be able to use in their trades. Indeed, a growing body of literature provides evidence of informed trading in non-own-company stock by financial insiders (e.g., Acharya and Johnson, 2007; Massa and Rehman, 2008; Bodnaruk, Massa, and Siminov, 2009; Acharya and Johnson, 2010; Ivashina and Sun, 2011; Massoud, Nandy, Saunders, and Song, 2011). Thus, if insiders in financial firms used their inside information, we would expect to observe better performance on not only their expertise trades, but also on their non-expertise stocks (trading firms outside their industry).

Table 7 shows little evidence to support this supposition. First, the subset of insiders in financial firms are not driving the expertise results, as financial firm insiders actually perform slightly worse on their expertise trades than non-financial insiders. Second, insiders in financial firms exhibit no outperformance for their non-expertise trades. For instance, the buy-minus-sell portfolio earns an insignificant 38 basis points in the three-month holding period.

Overall, the results again supports the notion that individuals who do not possess trading skill unconditionally, nevertheless possess skill in trading stocks in their specific areas of expertise. We view this as a strong test of the private information hypothesis because financial firm insiders are more likely than others to have direct access to other firms' non-public material information. The fact that their expertise trades do not earn abnormal returns provides further evidence that the performance of insiders' expertise trades is not likely to be driven by private information.

5.2.2 Trading Ahead of Merger Announcements?

We conduct additional tests to discriminate between the private and public information hypotheses. The extant literature primarily uses trading in the period leading up to an M&A announcement to test for the presence of trading on private information (e.g., Keown and Pinkerton, 1981; Cao, Chen, and Griffin, 2005; Bodnaruk, Massa, and Siminov, 2009; Griffin, Shu, and Topaloglu, 2012; Kedia and Zhou, 2014; Augustin, Brenner, and Subrahmanyam, 2015). In contrast to other corporate announcements, M&A announcements are typically completely unexpected events that lead to substantial price increases for target firms. Thus, they are a prime setting for exploiting private information. We, therefore, follow the prior literature by analyzing trading prior to M&A announcements.

In Table 8, we test whether insiders trade ahead of M&As within their industries, which would suggest that they are privy to private information about another firm in their industry. The table compares trading in target firms prior to M&A announcements for insider expertise trades, insider non-expertise trades, and all other retail traders. Panel A displays results for M&A announcements with positive cumulative abnormal return reactions on the two days around the announcement (t and t + 1) for the target firm, and Panel B displays results for large positive abnormal reactions (defined as announcement returns greater than 5%). Panels A and B indicate that there is very little trading in target firms prior to M&A announcements.

Panel B shows that there is only one instance in which an insider purchased the stock of another firm in her own industry in the 30 days before a meaningful M&A announcement was made (Panel B, Column (2), first row). Six non-expertise purchases took place before an M&A with a high abnormal reaction was announced (Panel B, Columns (1)–(3), second row). These numbers account for only a tiny fraction of the expertise and non-expertise trades (0.39% and 0.20%, respectively). In comparison, the percentage of purchases made by other retail investors that happened before an M&A (Panel B, Columns (1) to (3), third row) is 0.23%. Overall, corporate insiders do not appear to be more likely to place buy orders ahead of M&As than other retail traders are, regardless of whether the target is a firm in their industry.

To be cautious, we further analyze the one expertise trade that was placed before M&A activity. The purchase happened nine days before a friendly takeover, which was ultimately completed and led to the delisting of the target firm's shares about six months after the initial announcement. The insider realized the position before the delisting occurred and earned a round-trip return of 35%. However, the size of the trade was only about $20,000, which is less than the size of the average expertise trade. Moreover, the insider seems to have sold the stock too soon after the announcement, forfeiting a further potential gain of about 15%. For these reasons, it seems unlikely that this trade was based on private information.

Finally, we check the potential impact of this single trade by excluding it from the sample and find that it does not have any material effect on the results. These findings are not consistent with insiders actively trading on private information about other firms in their own industry.

5.2.3 Using Internal Information to Trade Other Firms?

Another possibility is that insiders trade on own-firm private information that is likely to have implications for other firms in the industry. For example, private information that own-firm earnings will be abnormally high might indicate increased industry profitability that can be exploited by trading in closely related firms.

In Table 9, we examine whether insiders' expertise trades potentially reflect trading on insider private information regarding their own firm. To test this hypothesis, we test whether expertise trades predict an insiders' own-firm earnings surprise. If insiders have private information regarding a shock to profitability for their own company, they may seek to exploit this information by trading in the stocks of closely related companies. For example, Tookes (2008) finds that information-based trades (inferred from order flows) in the stocks of competitors of announcing firms predict the announcing firms' returns.

In our test, we regress the own-firm earnings surprise on dummy variables that capture whether insider trades in the 45 or 15 days leading up to earnings announcement are in expertise or non-expertise stocks. If insiders are trading in the firms of their competitors as a means to exploit private information regarding their own firm, we would expect to find a significant expertise buy coefficient. Regardless of the specification in Table 9, we fail to find any economically or statistically significant coefficients on the expertise buy dummy variable. Furthermore, the signs of the other coefficients in the table seem to directly contradict the hypothesis that corporate insiders attempt to exploit information regarding their own firms' earnings announcements, since returns around earnings are higher after sales than they are after purchases.

5.2.4 Trading in Conjunction with Insider Trading?

We conjecture that trading in a specific firm that occurs in conjunction with insider trading at that firm might be a signal of private information. For instance, if expertise trading in Firm A by an insider in Firm B occurs contemporaneously with the trading of insiders in Firm A, then this potentially signals that the insider at Firm B is privy to private information regarding Firm A. Table 10 tests this hypothesis by investigating whether expertise buys (sells) are disproportionately more likely to occur in conjunction with insider trading buys (sells).

We examine the fraction of insider trading over our entire sample period that occurs in the window around an expertise trade. If expertise trades reflect private information, we would expect to find that a disproportionate amount of insider trading occurs in close proximity to expertise trades with the same sign. Panel A (Panel B) of Table 10 compares the fraction of insider trading purchases (sales) occurring around expertise trades to the fraction occurring around non-expertise trades and the trades of all other retail traders. We consider window lengths of three days, 15 days, and 31 days that are centered on the trading dates of expertise, non-expertise, and all other retail traders' trades. The results again fail to provide support for a private information story. Comparing the first row of Panel A to the second and third rows, we find that insider purchases are just as likely to occur in the window around expertise buys as they are to occur in the window around non-expertise buys and the buys of all other retail traders. The results hold for all window periods chosen. Moreover, comparing "buy" and "sell" columns in a given time window across the first row of Panel A, we find that insiders of the traded firms are not more likely to engage in insider trading purchases around expertise buys than they are around expertise sells. Panel B shows similar results: expertise sales do not take place in conjunction with insider trading sales.

We also examine the profitability of insider trades of economically linked firms. Using Compustat's historical customer segments file to identify customers or suppliers of insider firms, we find that less than 1% of trades in our sample are in trades of customers or suppliers. These few trades do not substantially contribute to the ability of insiders to outperform on expertise trades. Although fully ruling out the private information story is not possible, our results show no evidence that insiders exploit inside information in their trades. Rather, our findings suggest that insiders are able to more efficiently process public information than other traders.

6 Which Insiders Trade Profitably?

In this section, we briefly examine the characteristics of the insiders who trade most profitably. The insider population that is required to report their trades to the SEC under US law is composed of high level executives and members of boards of directors, as well as individuals who are more remote from the day-to-day operations, such as former or retired employees and shareholders with a large stake in the company. Our sample includes 12 individuals who reported their insider trades to the SEC during our sample period but were not working at any of the firms for which they were insiders.

We analyze, but do not report, the performance of this subsample of insiders. These individuals' trading behavior and performance in stocks outside their industry is similar to that of other insiders. However, they very rarely or never trade stocks inside their industry (only 7 purchases), and do so in an unprofitable manner. In fact, the insiders' trading skill in expertise stocks is entirely confined to trades made by insiders who were executives and directors at their firms at the time the trades were executed. We also find that the performance of insiders who are on the board of directors and do not hold any executive position is slightly weaker than that of executives, although the difference is not statistically significant.

7 Conclusion

We present the first analysis of insider trades in non-inside stocks. We show that insider trades disproportionately consist of stocks within the insider's industry of expertise. This trading tilt toward familiar stocks could represent a familiarity bias in which insiders invest in what they know. Alternatively, it could be the case that insiders possess a comparative advantage in trading stocks in their industry of expertise. We present evidence consistent with the latter, as insider trades in own-industry stocks vastly outperform trades in non-own-industry stocks.

In general, insiders are not skilled traders. However, our analysis shows that insiders do possess superior trading skill within their industry of expertise. This superior ability stems from stock picking rather than industry timing and is concentrated in stocks that are the hardest to value. The interpretation most consistent with our findings is that industry insiders have an advantage in processing public information regarding firms in their industry of expertise.

An interesting question is whether the documented effect is larger or smaller in recent years. On the one hand, due to increases in information dissemination, insiders might be less able to profit from their superior ability to process information. On the other hand, increased regulatory oversight of insider trading in recent years might cause insiders to increasingly focus their trading in own-industry stocks rather than in the stock of their own firm.

Appendix A. Matching Procedure of LDB and Insider Trading Filings

In this appendix, we show how we identify the trading accounts that belong to corporate insiders. To do so, we follow a three-step procedure to match the trades in the large discount broker (LDB) database and the SEC insider trading filings.

Step 1: Trade-level matches. We start by merging all the LDB common stock trades with the CRSP daily file. We have data on the quantity, price, date, and commission paid for each buy and sell transaction. We obtain the daily trading volume for each stock from CRSP. From the SEC filing, we obtain all the trades reported from January 1991 to November 1996; the data include purchase and sale quantities, dates, prices, and whether the transactions are related to the exercise of a stock option.

During the matching procedure, we do not aggregate trades at the daily level, because we need to consider three special cases. First, a purchase or a sale is occasionally split into two or more separate orders placed with the broker on the same day; if the transaction is indeed an insider's transaction, the insider might report to the SEC the separate transactions or the total amount. For this reason, we keep each single LDB trade and if in a given day an account has more than one transaction of the same stock of the same sign, we also create an auxiliary trade with the quantity equal to the total daily quantity.

Second, there are positions opened and closed within the same day; in the case of a corporate insider, this could indicate that a stock option has been exercised and the shares have been added to the account and then sold the very same day.

Third, a few orders that are initially written in the LDB books appear to go unexecuted and are later cancelled. These cases are characterized by negative commissions (i.e., the brokerage firm returns the commission fees to the clients whose orders have not been executed). Although it is possible to use an algorithm to adjust for these cases, for the purpose of a general analysis of the individuals' trading patterns, it is not immediately clear how to deal with them when the purpose is matching the trades with the SEC filing. For instance, suppose that on day t an insider places a buy order for 200 shares of stock A and another buy order for 300 shares of stock A. If then we learn that at day $t + 1$ the brokerage firm cancelled the purchase of 50 shares of stock A and gave back part of the commission to the insider, what should we expect the insider to have reported to the SEC? The strategy we adopt to deal with the three special cases presented above is designed to maximize the chances of finding possible matches in the first and second step of the procedure, allowing us to deal with the special cases when we manually double-check the matches one-by-one in step three.

The actual trade-level matching procedure begins with an approximate matching strategy. For each trade reported in the SEC filing, we find all the possible corresponding trades in the LDB database. A matched trade's quantity must lie within a 1% tolerance interval of the quantity reported to the SEC and must have been made no more than three days before or after the transaction date reported. This allows for cases in which, for instance, an insider's order is executed the day after it has been submitted, but the insider reported the order submission date as the transaction date. To avoid double-counting, we keep only the best match for each SEC trade-LDB account pair. At this stage, we also flag the matches for which the matched trade accounts for over 30% of the daily trading volume of the stocks.

Step 2: SEC insider-LDB account-level matches. At the end of the first step, there are several thousand potential matches. We next calculate a matching-likelihood score to restrict the search. The score calculated in this step is by no means the only criteria we use. Rather, its purpose is simply to screen the potential matches and eliminate the most unlikely ones. The formulas, parameters, and rules chosen should be understood accordingly.

We begin this step by counting how many trades have been matched for each SEC insider-LDB account pair; we call this variable tr_m. We also calculate the average absolute date difference and absolute percentage quantity difference between the trades reported in the SEC filing and the corresponding trades in the potentially matching LDB account; these variables are called $\overline{datediff}$ and $\overline{quantdiff}$. We also count how many trades in the sample period each insider reported to the SEC, including and excluding option-related transactions; the two variables are called, respectively, tr_{instot} and $tr_{insnoopt}$. Because it appears that option-related transactions are less likely to have been executed using the discount brokerage firm, we compute a variable to try to capture this fact when calculating the number of trades we expect to have been matched. This variable is called tr_{insw} and is computed as $0.5 \times tr_{instot} + 0.5 \times tr\_insnoopt$ if $tr_{insnoopt}$ is less than or equal to 3, and as $0.1 \times tr_{instot} + 0.9 \times tr\_insnoopt$ otherwise. We can now compute a variable that indicates the quality of the SEC insider-LDB account match as follows:

$$score_w = \frac{tr_m^2}{\sqrt{tr_{insw}}} \times \left(4 - \overline{datediff}\right)^2 \times \left(1 - \overline{quantdiff}\right)^{10} \tag{1}$$

The first term's purpose is twofold. First, through the numerator, it increases the score of potential matches for which the number of trades matched is higher. The numerator is quadratic because the higher the number of trades in a given trading account that perfectly match (by day, quantity, and sign) the trades of a given insider, the lower the probability that the insider and the discount broker client are two different individuals and that some of their trades are identical just by accident. Second, through the denominator, we decrease the score of potential matches for which the insider has made a large number of trades in his or her own firm during the sample period. This accounts for the fact that, ceteris paribus, it is more likely that another person's trade resembles some trades of the insider if the latter has made a larger number of trades. We use the square root of tr_{insw} because some insider trades reported to the SEC are not open-market transactions (e.g., the transaction price is missing or is very different from the prevailing market price), and so we should not expect that all trades reported to the SEC have been executed via the discount broker. The second and the third terms decrease the score if the SEC and LDB trades' dates or quantities do not match perfectly. We then keep only the SEC insiders-LDB account pairs that are more likely to be matches. If the number of trades matched (tr_m) is equal to or larger than 2, we require the score to be higher than 8. We also keep pairs that have a unique trade matched, as long as the date and quantity are perfectly matching and the insider filing contains less than six trades. We also carry to the next stage all the pairs that have a volume-flag. At this point, we have about 800 pairs that are potential matches.

Then, for each LDB account, we count the number of transactions in firms for which the potential matching corporate insider is indeed an insider and we call this variable tr_{ldbtot}. We adjust this variable to account for unexecuted trades, which, as explained above, are characterized by negative commission fees, and we do not count the auxiliary trades created in case a transaction has been executed with multiple orders within the same day. We can then evaluate the goodness of the potential matches from the LDB side. In theory, if the account really belongs to the corporate insider, all the transactions in the securities of their firms should have been reported in the SEC filing. However, this might not always be the case; for example, as explained above, it is possible that an insider's purchase or sale has been split into two or more orders, but she has reported a single transaction in the filing. In this case, our matching algorithm will have matched the transaction in the filing with the auxiliary total daily quantity expressly created for this purpose, and so tr_{ldbtot} will be larger than the actual number of trades matched tr_m. Taking into account these considerations, we modify the previously calculated score:

$$score_{tot} = score_w \times \left(\frac{tr_m - 0.35}{tr_{ldbtot}}\right)^3 \qquad (2)$$

We then carry to the third step only the pairs that have been assigned a total score greater than 0.5 or that have a volume flag.

Step 3: Manual matching. At the beginning of this step, we have 225 SEC insider-LDB account pairs. For each pair, we look at the trading patterns in the relevant stocks in the brokerage account and compare them against the trades reported in the SEC filing. This procedure allows us to make sure that the matching algorithm we employed produced sensible results.

One general requirement that we impose on the matches is that all trades made with the brokerage account must have been reported in full in the SEC filing. There can be exceptions to this rule if we believe that there is a good reason why the trades and the filing do not match. Specifically, we would classify as a good match a case in which all trades and the filing match except for the reported date of one of the transactions. In such a case, the insider has usually reported the transaction to have occurred one to five days after it has actually appeared in the LDB books. As long as the price reported in the filing and the purchase or sale price are the same despite the apparent date difference, we assume that either the shares have been deposited in the account a few days after the order was taken/executed or that the filing is not precise.

Finally, we consider as good matches the cases in which the insiders have reported the precise dates and quantities for all their trades but have reported purchase prices that, sometimes or always, are slightly higher than those recorded in the trading database. In these cases, it appears that the insiders reported the sum of the stock price plus the commissions paid as the purchase price.

Appendix B: Holdings-Based Calendar-Time Portfolio Methodology

Appendix A explains how we identify which trading accounts with stock transactions data in the large discount broker belong to corporate insiders. To supplement our analysis of their trading performance, we use daily buy and sell transactions from January 1991 to November 1996 to construct daily aggregate stock holdings for those insiders and for the remaining retail investors in the database. We start by netting out trades of the same stock made by a specific individual within the same day. At the end of the first trading day of January 1991, we use positive net quantity trades to back-out the positions. Starting from the second day of trading, we use both positive and negative net quantity transactions to update the holding positions, excluding sales made by individuals for whom we do not observe a previous corresponding purchase. At the beginning of each day, we adjust the positions for stock splits using the CFACSHR item from CRSP. Given that the average holding period in the database is one year, by the end of 1991 we have a fairly complete picture of the aggregate stock holdings of the individuals in the database. We do not know when the positions still held on November 1996 were closed, so in the holdings-based analysis we assume that these positions were held for the average holding period. Therefore, the time series we analyze goes from January 1991 to November 1997. Results are robust to the terminal holding period assumption. More importantly, because the number of stocks and the aggregate dollar amount in the holdings portfolios is smaller at the beginning of the sample, we show in Panel A of Table A2 that the results in Table 3 are robust to excluding 1991. As a further robustness check, Panel B of Table A2 repeats the regressions in Table 3 weighting each day in the time series by the aggregate dollar amount held in the portfolio at the end of the previous day, and Panel C of the same table repeats the same regressions weighting each day by the number of different stocks in the portfolio at the end of the previous day.

Appendix C: Transaction-Based Calendar-Time Portfolio Methodology

Motivated by the existing evidence that the stocks individual investors sell earn higher returns than those they buy (e.g., Odean, 1999), we test whether the same is true for the stocks traded by corporate insiders. In Table 4, we analyze the returns to calendar-time portfolios that mimic the buy and sell decisions of the insiders and of the other retail traders in the database. Following Seasholes and Zhu (2010), stocks purchased (sold) on day t are added to the buy (sell) portfolio at the beginning of day $t + 2$ and held for a period of 12 months, and positions are not rebalanced daily; that is, the relative weight of each position in the portfolio changes as stock prices change. In value-weighted (equal-weighted) portfolios, the initial value of each position in the portfolio is equal to the dollar value of the transaction that generated it (is equal to $1). Since the total number of trades made by insiders is considerably lower than the number of trades made by the other retail traders in the database and since trades are distributed unevenly across the sample period, in Table 4 we weight each daily return of the buy-and-sell portfolio by the number of trades contributing to the portfolio in that specific day. The daily weight for the buy-minus-sell return is calculated as 0.5 times the relative daily weight in the buy portfolio's time series plus 0.5 times the relative daily weight in the sell portfolio's time series. Due to the weighting scheme, the average buy-minus-sell return can vary slightly from the difference between the average buy and the average sell return. Moreover, whenever the number of stocks N in a buy or a sell portfolio is less than 5, the portfolio return is determined as 20%*N times the average return of the N stocks in the portfolio plus 20%*(5 – N) times the market return.

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Figure 1. Characteristics-Adjusted Returns – Buys

This figure shows event-time buy-and-hold DGTW-adjusted returns for portfolios mimicking the purchases of corporate insiders and other retail traders in the LDB database for 63 trading days after portfolio formation. Trade categories are defined in Table 3.

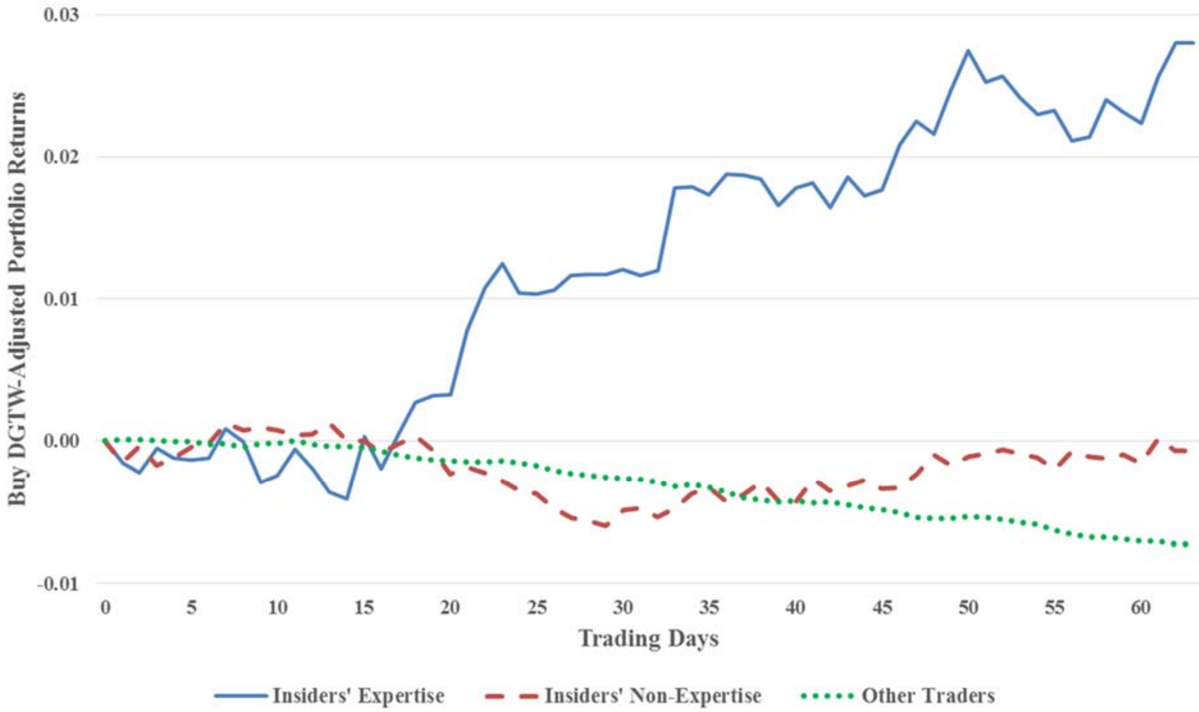

Figure 2. Buy-Minus-Sell Portfolios

This figure shows event-time DGTW-adjusted return differences between buy and sell portfolios mimicking purchases and sales of corporate insiders and other retail traders in the LDB database for 63 trading days after portfolio formation. Trade categories are defined in Table 3.

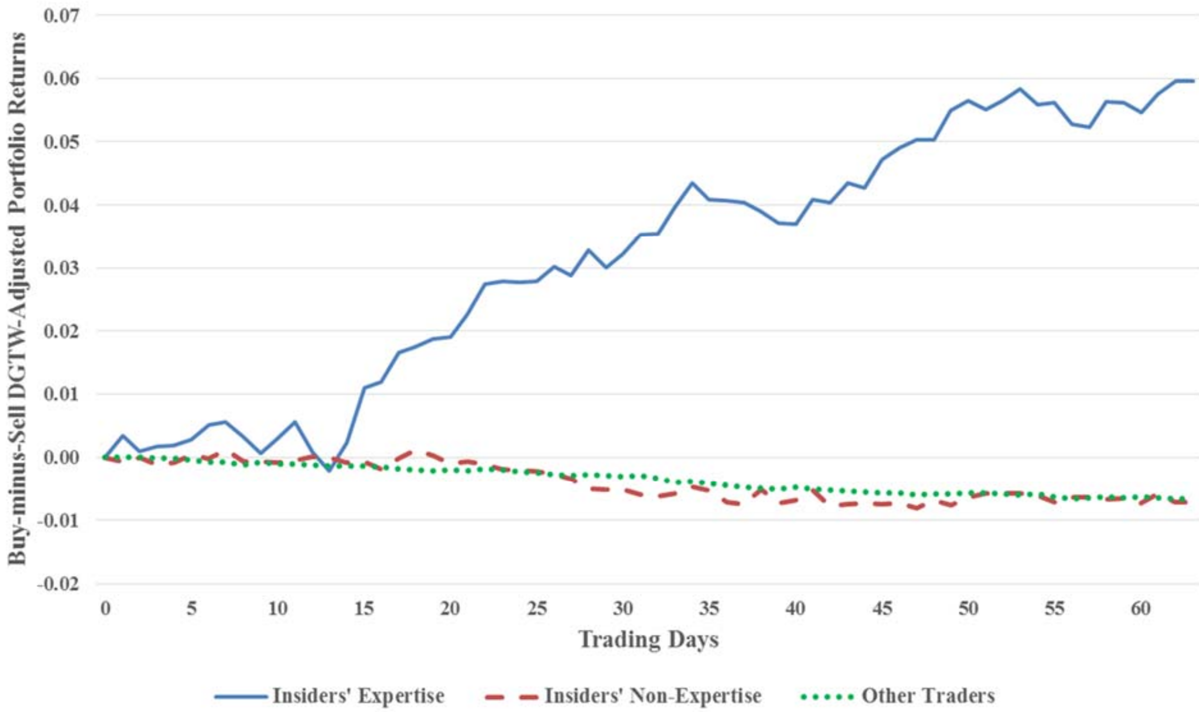

Figure 3. Do Insiders Know When to Drop a Stock?

Figure 3a shows the percentage of stock positions closed as a function of the number of trading days elapsed since they were opened. Figure 3b measures the improvement in trader performance arising due to the timing of sales. The figure shows the difference in DGTW-adjusted returns between buy-hold-drop and buy-hold portfolios for insiders' expertise trades, insiders' non-expertise trades, and the trades of other retail traders for 100 trading days. Buy-hold-drop portfolios are rebalanced each day by dropping the stocks sold during the previous day. Trade categories are defined in Table 3.

Figure 3a. Percentage of Stock Positions Closed as a Function of Holding Period

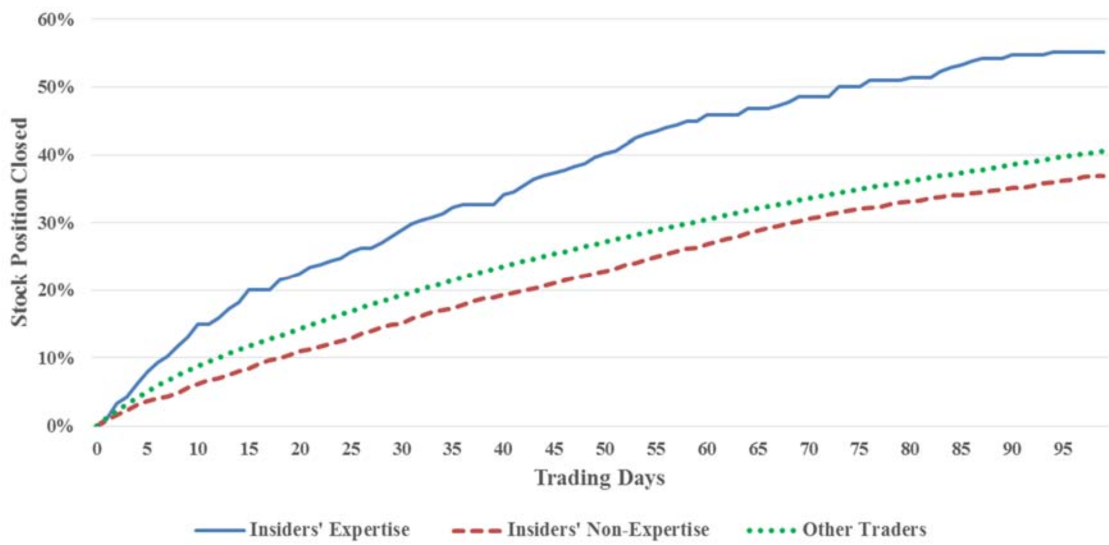

Figure 3b. Buy-Hold-Drop Minus Buy-and-Hold Portfolio Returns

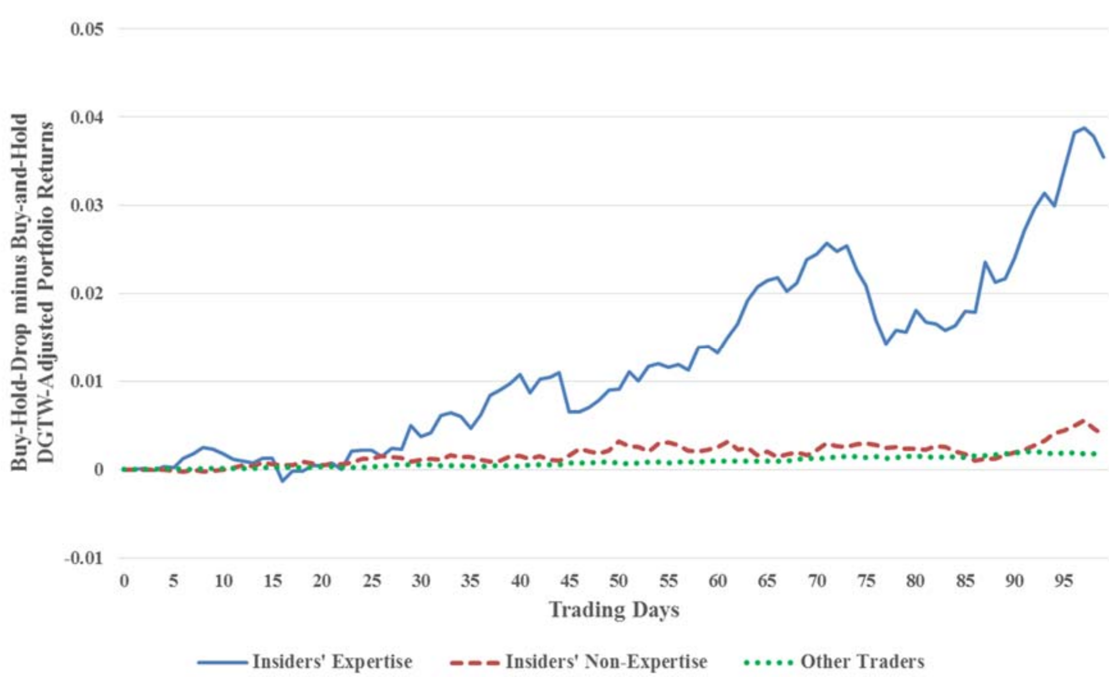

Figure 4. Insiders' Expertise Trades and Earnings Announcements

This figure plots the subsequent cumulative average abnormal returns around earnings announcements for stocks traded by insiders. CARs are set to 0 at $t = -2$ trading days. For each stock, we measure the net quantity traded by each insider between earnings announcements (excluding the day of announcement and day prior to announcement). Stocks with positive (negative) traded quantities are added to the buy (sell) portfolio. We plot CARs for earnings announcements following expertise buys, expertise sells, and non-expertise buys. For comparison purposes, we also plot the CAR for earnings announcements of the stocks traded that are not preceded by an insider's trade.

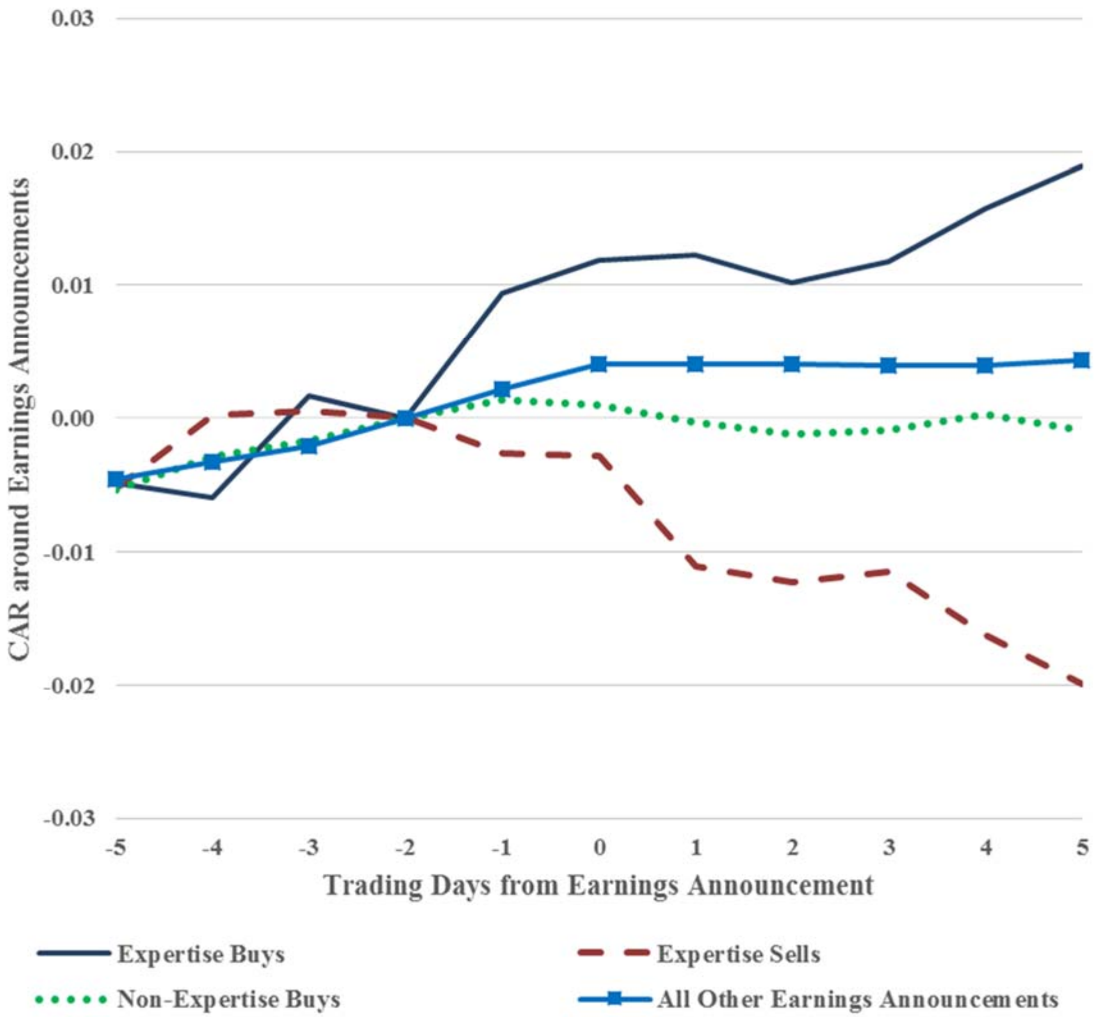

Table 1. Summary Statistics

This table presents summary statistics for the individuals in our sample of 105 corporate insiders and for all other retail traders in the large discount broker (LDB) dataset from January 1991 to November 1996. Total Number of Firms is the number of companies for which those individuals are insiders. Insiders' Expertise Trades are trades made by corporate insiders in firms in their own industry other than their own firm. We use the three-digit SIC code industry definition. Insiders' Non-Expertise Trades are trades made by corporate insiders outside of their industry. All Other Retail Traders are all the trades made by all other individual traders in the LDB database. In Panel A, Firms' Market Cap is the average end-of-June market capitalization of the insiders' firms, and Firms' NYSE-AMEX Percentile is the average end-of-June NYSE-AMEX percentile of the insiders' firms. If an individual is an insider for more than 1 firm, we only use the largest when calculating the two statistics described immediately above. In Panel C, stocks are assigned to size and book-to-market quintiles based on the Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) breakpoints and to previous-month return quintiles based on AMEX, NASDAQ, and NYSE breakpoints. We include all trades of at least $100 in common shares (share code 10 or 11) of AMEX, NASDAQ, and NYSE firms that have a valid five-digit SIC code and a DGTW assignment. Please refer to the text for further details.

Panel A: Summary Statistics for Insiders and Their Firms

Panel A : Summary Stats for Insiders and their Companies

	N	Mean	Std. Dev.	Min	25%	50%	75%	Max
Number of Individuals	105							
Total Number of Firms	171							
Number of Firms by Individual	105	1.63	1.27	1	1	1	2	7
Firms' Market Cap ($1,000)	105	1,803,781	4,895,634	5,114	51,088	208,301	1,198,165	33,612,047
Firms' NYSE-AMEX Percentile	105	47.70	27.90	0	24	46	67	99

	Insiders in Each Industry	
	N	%
Financials	25	14.6
Computer Hardware	13	7.6
Business Services	9	5.3
Oil & Gas	8	4.7
Retail	7	4.1

Panel B: Trade Size by Trade Type

	Trade Size Statistics ($)									
	N	Mean	Std. Dev.	Min	5%	25%	50%	75%	95%	Max
Insiders' Trades in Own Firm	785	61,374	197,594	109	1,563	5,625	11,500	35,000	228,373	2,498,438
Insiders' Expertise Trades	416	27,656	76,535	156	1,475	4,528	9,550	24,225	91,000	823,975
Insiders' Non-Expertise Trades	4,258	20,979	65,384	100	1,625	4,250	7,684	17,000	61,500	1,499,595
All Other Retail Traders	1,418,559	13,174	36,871	100	963	2,850	5,650	12,344	46,101	6,094,704

Panel C: Buy Trade Characteristics

	% of Trades in Low and High Quintiles						
		Size		B/M		t-1 Return	
	N	Low	High	Low	High	Low	High
Insiders' Expertise Trades	214	22.9	42.5	31.3	10.3	16.8	22.9
Insiders' Non-Expertise Trades	2,302	18.6	40.0	40.9	13.0	18.3	19.3
All Other Retail Traders	764,325	17.7	41.1	37.7	13.9	19.7	19.9

Table 2. Trading Tilt Toward Expertise Stocks

In this table, we analyze whether corporate insiders tend to trade stocks of other firms in their own industry. A stock purchase or sale by a corporate insider is classified as Expertise if the stock is in the insider's industry based on the three-digit SIC code definition. Trades in an insider's own firm are excluded. For each corporate insider, the benchmark is the fraction of trades that we would expect to be expertise trades if the individual had no trading tilt toward stocks in his/her own industry. In Panel A (Panel B), the NYSE, AMEX, NASDAQ-benchmarked expected percentage is calculated as the fraction of (the market capitalization of) NYSE, AMEX, and NASDAQ stocks that are in an insider's industry. Further, in Panel A (Panel B), the Other Retail Traders-benchmarked expected percentage is calculated as the (dollar-weighted) fraction of trades that all the non-insider individual investors in the LDB database make in an insider's industry. If an individual is an insider in more than one industry, we sum those industries' fractions to calculate the expected percentage. In Panel A (Panel B), the actual percentage is simply the observed (dollar-weighted) percentage of an insider's expertise trades. The tilt is the difference between the actual and the expected percentages. *** indicates statistical significance at the 1% level.

Panel A: Trades Are Equal Weighted

Panel A: Equal Weighted				
	Averaged across Trades		Averaged across Traders	
Benchmark:	NYSE, AMEX, NASDAQ	Other Retail Traders	NYSE, AMEX, NASDAQ	Other Retail Traders
	(1)	(2)	(3)	(4)
Percentage of Expertise Trades				
Benchmark (%)	4.09	4.23	3.33	3.83
Actual (%)	8.39	8.39	11.01	11.01
Tilt = Actual - Benchmark (%)	4.31***	4.17***	7.69***	7.18***
Tilt t-stat	(12.14)	(11.67)	(3.57)	(3.29)
Tilt ratio = Actual / Expected	2.05	1.99	3.31	2.87

Panel B: Trades Are Dollar Weighted

	Averaged across Trades		Averaged across Traders	
Benchmark:	NYSE, AMEX, NASDAQ	Other Retail Traders	NYSE, AMEX, NASDAQ	Other Retail Traders
	(1)	(2)	(3)	(4)
Percentage of Expertise Trades				
Benchmark (%)	3.82	4.58	3.21	4.24
Actual (%)	10.38	10.38	10.53	10.53
Tilt = Actual - Benchmark (%)	6.56***	5.80***	7.32***	6.29***
Tilt t-stat	(16.81)	(14.74)	(3.40)	(2.86)
Tilt ratio = Actual / Expected	2.72	2.26	3.28	2.48

Table 3. Expertise Trades: Holdings-Based Calendar-Time Portfolios

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. Retail Traders indicate trades made by the other individuals in the Large Discount Broker (LDB) dataset. In this table, we analyze the performance of holdings-based portfolios. We construct aggregate daily holding positions from the daily buy and sell transaction data. Portfolio returns are value-weighted. Please see Appendix B for details. In Panel A, we present average raw returns by calendar year. The market return is the market return in the Fama-French (1993) model. In Panel B, we report alphas from calendar-time regressions of the holdings-based returns in excess of the risk-free rate on the Fama-French (1993), Carhart (1997), Hou, Xue, and Zhang (HXZ) (2014) and Fama-French (2015) factors. *t*-statistics based on Newey-West (1987) standard errors with five lags and robust to heteroskedasticity and serial correlation are in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

Panel A: Raw Returns (Basis Points per Day)

			Insiders' Trades		
	Market Return	Retail Traders	All	Expertise	Non-Expertise
	(1)	(2)	(3)	(4)	(5)
1991	12.6	14.8	18.9	31.1	17.1
1992	3.8	3.1	0.5	9.8	-0.7
1993	4.3	3.6	5.5	4.4	5.7
1994	0.1	1.2	4.4	3.8	4.6
1995	12.5	12.4	11.3	12.7	11.6
1996	7.8	8.3	11.1	15.5	10.5
1997	11.5	11.6	12.4	16.5	12.2
All Years	7.5	7.8	9.1	13.2	8.7

Panel B: Factor Regression Alphas (Basis Points per Day)

		Insiders' Trades		
	Retail Traders	All	Expertise	Non-Expertise
	(1)	(2)	(3)	(4)
Fama-French 3 Factor Model	0.14	1.20	5.40**	0.74
	(0.26)	(0.89)	(2.13)	(0.52)
Carhart 4 Factor Model	0.24	1.15	5.81**	0.68
	(0.46)	(0.87)	(2.24)	(0.48)
HXZ Q-Factor Model	-0.01	0.95	4.90*	0.54
	(-0.02)	(0.71)	(1.92)	(0.38)
Fama-French 5 Factor Model	0.56	1.74	5.19**	1.36
	(1.12)	(1.22)	(2.00)	(0.90)

Table 4. Expertise Trades: Transactions-Based Buy-Minus-Sell Calendar-Time Portfolios

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, and the insider's remaining trades are defined as Non-Expertise. All Retail Traders indicates trades made by the other individuals in the Large Discount Broker (LDB) dataset. In this table, we analyze the performance of transaction-based buy and sell calendar-time portfolios with a 12-month holding period. Each day in the time series of each portfolio return is weighted by the number of trades contributing to the portfolio in that specific day. Annual Difference is the annualized average buy-minus-sell portfolio return. Annual Alpha is the annualized alpha from a calendar-time regression of the buy-minus-sell portfolio return on the Carhart (1997) factors. *t*-statistics based on Newey-West (1987) standard errors with five lags and robust to heteroskedasticity and serial correlation are in parentheses.

Panel A: Value-Weighted Portfolios, 12-Month Holding Period

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	10.33	4.19	15.07**	2.48	15.97***	2.67
Insiders' Non-Expertise	6.83	6.02	2.57	0.76	3.01	0.88
All Retail Traders	6.93	7.76	-2.11***	-2.88	-0.36	-0.59

Panel B: Equal-Weighted Portfolios, 12-Month Holding Period

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	10.21	6.46	8.57*	1.77	11.02**	2.26
Insiders' Non-Expertise	6.33	6.82	-0.79	-0.44	0.90	0.52
All Retail Traders	6.26	7.18	-2.33***	-2.72	-0.44	-0.66

Table 5. Buy-and-Hold Abnormal Returns, 3 months

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. All Retail Traders' Trades indicates trades made by the other individuals in the Large Discount Broker (LDB) dataset. We report three-month (63 days) buy-and-hold returns as well as returns in excess of the DGTW benchmark return and the value-weighted industry benchmark returns. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

		Equal Weighted			Trade-Size Weighted		
		Raw	DGTW-Adjusted	Industry-Adjusted	Raw	DGTW-Adjusted	Industry-Adjusted
		(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise Trades (Exp)	Buy	7.39***	2.76*	2.29	12.96***	5.52***	5.12***
		(4.23)	(1.66)	(1.41)	(7.14)	(3.10)	(3.17)
	Sell	1.43	-3.11*	-2.08	-2.30	-5.99***	-5.48***
		(0.76)	(-1.90)	(-1.24)	(-1.19)	(-3.54)	(-3.52)
	Buy - Sell	5.96**	5.87**	4.38*	15.26***	11.51***	10.60***
		(2.33)	(2.52)	(1.87)	(5.76)	(4.69)	(4.73)
Insiders' Non-Expertise Trades (Nexp)	Buy	3.80***	-0.19	-0.91**	5.94***	1.66***	1.28***
		(8.06)	(-0.45)	(-2.10)	(12.77)	(3.99)	(3.11)
	Sell	5.00***	0.46	0.46	4.91***	0.21	0.47
		(9.63)	(0.99)	(0.98)	(11.28)	(0.55)	(1.23)
	Buy - Sell	-1.20*	-0.66	-1.36**	1.02	1.45**	0.81
		(-1.71)	(-1.03)	(-2.14)	(1.61)	(2.53)	(1.44)
All Retail Traders' Trades (RT)	Buy	3.30***	-0.85***	-0.85***	3.26***	-0.90***	-0.87***
		(125.37)	(-36.20)	(-36.01)	(128.25)	(-39.80)	(-38.59)
	Sell	3.88***	-0.31***	-0.26***	3.90***	-0.33***	-0.36***
		(142.65)	(-12.68)	(-10.79)	(147.60)	(-14.11)	(-15.75)
	Buy - Sell	-0.59***	-0.54***	-0.59***	-0.63***	-0.57***	-0.50***
		(-15.50)	(-16.04)	(-17.29)	(-17.32)	(-17.56)	(-15.55)

Table 6. Expertise Trades in Hard-to-Value Stocks

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. Retail Traders indicates trades made by the other individuals in the Large Discount Broker (LDB) dataset. We sort buy and sell trades into two equally-sized portfolios using the in-sample median value of stock size, residual analyst coverage calculated as in Hong, Lim and Stein (2000), and idiosyncratic volatility calculated in month t-1, following Ang, Hodrick, Xing, and Zhang (2006). The median expertise stock is in the 72nd NYSE-AMEX size percentile. Three-month equal-weighted DGTW-adjusted excess returns are reported. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

Panel A: Expertise Trades and Hard-to-Value Stocks: Size

	Insiders' Trades			Retail Traders			
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy	Differences		
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Firm Size							
Low	4.02	-8.79***	-0.65	-1.34***	12.82***	4.68	5.36*
	(1.35)	(-3.21)	(-0.89)	(-33.35)	(3.17)	(1.52)	(1.80)
High	1.49	2.64*	0.27	-0.36***	-1.15	1.22	1.85
	(1.03)	(1.67)	(0.58)	(-14.85)	(-0.53)	(0.80)	(1.27)
Low - High	2.54	-11.43***	-0.92	-0.97***	13.97***	3.46	3.51
	(0.77)	(-3.61)	(-1.06)	(-20.77)	(3.05)	(1.01)	(1.06)

Panel B: Expertise Trades and Hard-to-Value Stocks: Residual Analyst Coverage

	Insiders' Trades			Retail Traders			
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy	Differences		
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Resid. Analyst Coverage							
Low	3.21	-5.30**	-0.75	-1.47***	8.51**	3.95	4.68*
	(1.26)	(-2.14)	(-1.23)	(-44.61)	(2.39)	(1.51)	(1.83)
High	2.31	-0.89	0.36	-0.23***	3.20	1.96	2.54
	(1.09)	(-0.42)	(0.58)	(-6.85)	(1.07)	(0.88)	(1.19)
Low - High	0.89	-4.41	-1.10	-1.24***	5.31	1.99	2.13
	(0.27)	(-1.35)	(-1.27)	(-26.48)	(1.14)	(0.58)	(0.64)

Table 6. Expertise Trades in Hard-to-Value Stocks (Cont.)

Panel C: Expertise Trades and Hard-to-Value Stocks: Idiosyncratic Volatility

	Insiders' Trades			Retail Traders	Differences		
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy			
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Idiosyncratic Volatility							
High	3.07	-7.68***	-1.49**	-1.78***	10.74***	4.56	4.85
	(1.00)	(-2.73)	(-1.98)	(-43.27)	(2.58)	(1.44)	(1.58)
Low	2.47*	1.42	1.10***	0.08***	1.06	1.37	2.39*
	(1.76)	(0.90)	(2.58)	(3.56)	(0.50)	(0.93)	(1.70)
High - Low	0.59	-9.10***	-2.60***	-1.86***	9.69**	3.19	2.45
	(0.18)	(-2.82)	(-3.00)	(-39.67)	(2.07)	(0.91)	(0.73)

Table 7. Financial Firm Insiders

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. Financial Firm Insiders are individuals who are insiders of at least one financial firm or bank, according to the 49 Fama-French industry definition. 23 out of 105 corporate insiders in our sample are classified as Financial Firm Insiders, and they are responsible for roughly 30% of insiders' trades. The remaining insiders are classified as Non-Financial Firm Insiders. Three-month equal-weighted DGTW-adjusted excess returns are reported. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

	All Insiders	Financial Firms Insiders	Non-Financial Firms Insiders
	(1)	(2)	(3)
N (#insiders)	105	23	82
Expertise Buy	2.76*	1.17	4.15
	(1.66)	(0.87)	(1.44)
Expertise Sell	-3.11*	0.30	-5.70**
	(-1.90)	(0.15)	(-2.34)
Expertise Buy - Sell	5.87**	0.87	9.85***
	(2.52)	(0.36)	(2.61)
Non-Expertise Buy	-0.19	1.21*	-1.30**
	(-0.45)	(1.85)	(-2.25)
Non-Expertise Sell	0.46	0.83	0.23
	(0.99)	(1.14)	(0.38)
Non-Expertise Buy - Sell	-0.66	0.38	-1.54*
	(-1.03)	(0.39)	(-1.82)

Table 8. Insiders' Trades around M&A Announcements

In this table, we analyze whether corporate insiders tend to trade ahead of mergers and acquisitions in firms in their own industry (Expertise trades) or in other industries (Non-Expertise trades) based on the three-digit SIC code definition. We also report the same statistics for the other Retail Traders in the LDB database. We display the number of purchases made 1 to 5, 6 to 15, and 16 to 30 calendar days before and after the initial announcement, for stocks that are the target of M&A activity. Data for merger and acquisition announcements from 1991 to 1996 are from Securities Data Company (SDC). We include announcements of deals that have been completed, as well as of those that have not. In Panel A (Panel B), we only include M&A announcements in which the target's abnormal stock return the day of the announcement and the following trading days was higher than 0% (5%).

Panel A: Number of Buy Trades Around M&A Announcements with Abnormal Ret > 0%

	Days around M&A Announcements					
	-30 to -16	-15 to -6	-5 to - 1	1 to 5	6 to 15	16 to 30
	(1)	(2)	(3)	(4)	(5)	(6)
# Insiders' Expertise Trades	0	1	1	3	0	1
% of total Expertise Trades	0.00	0.39	0.39	1.16	0.00	0.39
# Insiders' Non-Expertise Trades	5	3	1	8	5	6
% of total Non-Expertise Trades	0.16	0.10	0.03	0.26	0.16	0.20
# Retail Traders Trades	1371	985	423	1262	876	1053
% of total Retail Traders Trades	0.14	0.10	0.04	0.13	0.09	0.11

Panel B: Number of Buy Trades Around M&A Announcements with Abnormal Ret > 5%

	Days around M&A Announcements					
	-30 to -16	-15 to -6	-5 to - 1	1 to 5	6 to 15	16 to 30
	(1)	(2)	(3)	(4)	(5)	(6)
# Insiders' Expertise Trades	0	1	0	2	0	0
% of total Expertise Trades	0.00	0.39	0.00	0.77	0.00	0.00
# Insiders' Non-Expertise Trades	2	3	1	7	3	2
% of total Non-Expertise Trades	0.07	0.10	0.03	0.23	0.10	0.07
# Retail Traders Trades	1096	787	329	1049	641	708
% of total Retail Traders Trades	0.11	0.08	0.03	0.11	0.07	0.07

Table 9. Do Insiders Exploit Own Firm Earnings Information?

In this table, we test whether corporate insiders attempt to profit from their knowledge of their own-firm earnings by trading stocks of other firms in the same industry ahead of their own firm's earnings announcements. A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. The dependent variable in all regression specifications in this table is the cumulative abnormal return (CAR) from one trading day before to one trading day after an earnings announcement of an insider's own firm. We use the market value-weighted return as the benchmark. We include all earnings announcements from January 1991 to January 1997. We regress CARs on indicators for expertise and non-expertise trades. We use two different rules to determine the sign of the indicators within each category. Under the first rule (Columns (1) and (3)), the expertise (non-expertise) buy indicator equals 1 and the expertise (non-expertise) sell indicator equals 0 if the net dollar quantity of stocks in this category traded before a given earnings announcement is positive, and vice versa if negative. Under the second rule (Columns (2) and (4)), we use only the sign of the last trade of each category (i.e., expertise or non-expertise) to determine the value of the indicators. In Column (1) and (2) ((3) and (4)), we determine the values of the indicators based on the trades made between 45 days and 1 day before each given earnings announcement. In Column (3) and (4), we determine the values of the indicators based on the trades made between 15 days and 1 day before each given earnings announcement. In all specifications we include a set of control variables: the lagged CAR, the lagged one-month stock return, the log of the firm's market capitalization and book-to-market ratio, and the inverse of the stock price. All variables are winsorized at the 1% level. *t*-statistics based on White (1980) heteroscedasticity-consistent standard errors are in parenthesis.

Dependent variable:	CAR (-1, +1) Around Own-Firm's Earning Announcement			
	(1)	(2)	(3)	(4)
Expertise Buy	-0.28	-0.25	-0.24	-0.08
	(-0.32)	(-0.29)	(-0.15)	(-0.05)
Expertise Sell	0.68	0.63	1.01	0.85
	(0.83)	(0.75)	(0.88)	(0.72)
Non-Expertise Buy	-0.31	-0.45	-0.12	-0.21
	(-0.87)	(-1.27)	(-0.26)	(-0.48)
Non-Expertise Sell	0.30	0.55	-0.07	0.09
	(0.72)	(1.28)	(-0.13)	(0.17)
Controls	Yes	Yes	Yes	Yes
Days Before Announcement	45	45	15	15
Indicators Rule	Net	Last	Net	Last
Obs.	2684	2684	2684	2684
Adj. R^2	0.00	0.00	0.00	0.00

Table 10. Trading in Conjunction with Other Firms' Insiders?

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the remaining trades are classified as non-expertise. All Retail Traders indicates trades made by other individuals in the Large Discount Broker (LDB) dataset. For each window considered, the Insider Trading Purchase (Sale) Ratio is calculated with the SEC insider trading filings using the following procedure. Each day *t*, for each stock in CRSP, we calculate the number of that firm's insiders purchasing (selling) their own firm's stock. We divide this number by the total number of insider purchases (sales) in that stock over our sample period (January 1991 to November 1996). Finally, we sum this fraction over the window. We consider three different windows of 3 days, 15 days, and 31 days centered on the date of the Expertise trade, Non-Expertise trade, or Other Retail Traders trade.

Panel A: Average Insider Trading Purchase Ratio (%)

Window around trades:	± 1 Days		± 7 Days		± 15 Days	
	Buy	Sell	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	0.15	0.17	0.60	0.78	1.49	1.58
Insiders' Non-Expertise	0.22	0.16	0.75	0.67	1.58	1.33
Other Retail Traders	0.17	0.15	0.74	0.67	1.49	1.37

Panel B: Average Insider Trading Sale Ratio (%)

Window around trades:	± 1 Days		± 7 Days		± 15 Days	
	Buy	Sell	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	0.17	0.12	0.92	0.62	1.51	1.40
Insiders' Non-Expertise	0.23	0.22	0.93	0.86	1.87	1.74
Other Retail Traders	0.20	0.21	0.79	0.84	1.57	1.67

Internet Appendix

Table A1. Round-trip Returns and Monthly Based Returns

In this table, we present the equal-weighted round-trip returns earned by corporate insiders and other retail traders on their purchases. We separate purchases into two groups depending on whether they were closed within 63 trading days of their opening. The average number of trading days in a month during our sample period is 21.08, so we use 63 trading days as an approximation for a three-month period. For positions closed within 63 trading days, we calculate the realized return as the cumulated return earned starting the day after the purchase until the day of the sale. For positions held for more than 63 trading days, we report the 63 trading days' cumulated return, calculated starting the day after the purchase. The Average 63 Trading Days Return (Realized or Trailing) is computed using the round-trip returns for the positions that are closed within 63 days, and the 63 trading day returns for the remaining positions. Equivalent 3-Month Average Return is the Average 63 Trading Days (Realized or Trailing) adjusted for the average difference between the Average Holding Period and the actual number of trading days in a three-month period. We exclude purchases made in the last 63 trading days of our 5 year and 11 month sample, because it is not possible to determine when some of the resulting positions were closed. The number of observations used in this table is therefore about 4% smaller than in Table 1. See the text for further details.

	Insiders' Expertise Trades	Insiders' Non-Expertise Trades	All Other Retail Traders
	(1)	(2)	(3)
All Positions			
Observations	209	2,176	729,284
Average Holding Period (Capped at 64 Trading Days)	46.1	54.9	52.6
Average 63 Trading Days Return (Realized or Trailing)	5.8	3.7	3.0
Equivalent 3 Month Average Return	7.91	4.29	3.63
Average 3 Month Returns Calculated as in Table 5	7.39	3.80	3.30
Positions Closed Within 63 Trading Days of Purchase			
Observations	95	547	215,932
Percent of Total Purchases (%)	45.5	25.1	29.6
Average Holding Period (Trading Days)	24.7	27.9	25.6
Average Round-trip Return (Realized)	5.04	5.01	5.65
Positions Held For More Than 63 Trading Days			
Observations	114	1,629	513,352
Percent of Total Purchases (%)	54.5	74.9	70.4
Average Return After 63 Trading Days (Trailing)	6.38	3.30	1.92

Table A2. Holdings-Based Calendar-Time Portfolios

This table presents robustness tests for Table 3, Panel B under different specifications. Panel A replicates the analysis excluding year 1991 from the time series of portfolio returns. In panel B (panel C), each observation in the regression, i.e., each day in the time series of portfolio returns, is weighted by the aggregate dollar amount held in the portfolio at the end of the previous day (by the number of different stocks in the portfolio at the end of the previous day). Panel D replicates the analysis in Table 3, Panel C excluding microcap stocks, defined as stocks in the lowest DGTW size quintile.

Panel A: Excluding 1991

	All Retail Traders	All Insiders's Traders	Insiders' Expertise Trades	Insiders' Non-Expertise Trades
	(1)	(2)	(3)	(4)
Fama-French 3 Factor Model	0.58	1.56	5.14**	1.33
	(1.03)	(1.51)	(2.08)	(1.24)
Carhart 4 Factor Model	0.65	1.54	5.00**	1.32
	(1.16)	(1.49)	(2.02)	(1.23)
HXZ Q-Factor Model	0.18	0.84	4.07*	0.59
	(0.30)	(0.77)	(1.67)	(0.52)
Fama-French 5 Factor Model	1.04**	2.18**	5.31**	2.06*
	(1.97)	(2.04)	(2.10)	(1.86)

Panel B: Days Weighted by Aggregate Dollar Amount

	All Retail Traders	All Insiders's Traders	Insiders' Expertise Trades	Insiders' Non-Expertise Trades
	(1)	(2)	(3)	(4)
Fama-French 3 Factor Model	0.50	1.91*	5.58**	1.78*
	(0.83)	(1.85)	(2.23)	(1.66)
Carhart 4 Factor Model	0.57	1.90*	5.28**	1.79*
	(0.94)	(1.85)	(2.13)	(1.67)
HXZ Q-Factor Model	-0.15	1.40	4.65*	1.25
	(-0.24)	(1.36)	(1.81)	(1.17)
Fama-French 5 Factor Model	0.91	2.40**	5.68**	2.41**
	(1.65)	(2.29)	(2.23)	(2.22)

Table A2. Holdings-Based Calendar-Time Portfolios (Cont.)

Panel C: Days Weighted by Number of Stocks in Portfolio

	All Retail Traders	All Insiders's Traders	Insiders' Expertise Trades	Insiders' Non-Expertise Trades
	(1)	(2)	(3)	(4)
Fama-French 3 Factor Model	0.26	1.63*	4.76**	1.44
	(0.49)	(1.67)	(2.09)	(1.42)
Carhart 4 Factor Model	0.35	1.61	4.55**	1.43
	(0.65)	(1.64)	(2.01)	(1.41)
HXZ Q-Factor Model	0.00	1.24	3.54	1.05
	(-0.01)	(1.23)	(1.56)	(0.99)
Fama-French 5 Factor Model	0.70	2.17**	4.66**	2.09**
	(1.38)	(2.14)	(2.04)	(1.98)

Panel D: Excluding Microcaps

	All Retail Traders	All Insiders's Traders	Insiders' Expertise Trades	Insiders' Non-Expertise Trades
	(1)	(2)	(3)	(4)
Fama-French 3 Factor Model	0.36	1.56	5.87**	0.99
	(0.64)	(1.12)	(2.40)	(0.67)
Carhart 4 Factor Model	0.47	1.49	5.66**	0.95
	(0.85)	(1.08)	(2.32)	(0.65)
HXZ Q-Factor Model	0.07	1.12	4.83*	0.64
	(0.12)	(0.81)	(2.00)	(0.43)
Fama-French 5 Factor Model	0.69	1.99	6.27**	1.45
	(1.30)	(1.35)	(2.51)	(0.93)

Table A3. Transactions-Based Calendar-Time Portfolios

This table presents robustness tests for Table 4 under different specifications. Panel A and B report figures computed analogously to, respectively, Table 4, Panel A and Table 4, Panel B, with the only exception being that each observation, i.e., each day in the time series of portfolio returns, is weighted by the aggregate dollar amount held in the portfolio at the end of the previous day. Panel C and D replicate the analysis presented in Table 4 excluding microcap stocks, defined as stocks in the lowest DGTW size quintile. Panel E and F replicate the analysis presented in Table 4 using a 6-month holding period. Panel G and H replicate the analysis presented in Table 4 using a 3-month holding period.

Panel A: Value-Weighted Portfolios, Days Weighted by Aggregate Dollar Amount

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	12.06	2.51	19.75***	2.73	19.39***	2.71
Insiders' Non-Expertise	6.57	5.50	2.76	0.78	3.11	0.89
All Retail Traders	6.83	7.74	-2.07***	-2.63	-0.34	-0.51

Panel B: Equal-Weighted Portfolios, Days Weighted by Aggregate Dollar Amount

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	10.32	5.40	11.20*	1.86	12.61**	2.11
Insiders' Non-Expertise	5.92	6.20	-0.74	-0.40	0.86	0.49
All Retail Traders	6.27	7.22	-2.23**	-2.40	-0.40	-0.56

Panel C: Value-Weighted Portfolios, Excluding Microcaps

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	10.79	4.09	20.00***	3.30	20.92***	3.53
Insiders' Non-Expertise	7.37	6.30	3.53	1.04	3.46	1.01
All Retail Traders	7.18	7.96	-2.00***	-2.60	-0.20	-0.31

Table A3. Transactions-Based Calendar-Time Portfolios (Cont.)

Panel D: Equal-Weighted Portfolios, Excluding Microcaps

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	8.90	7.31	5.94	1.40	8.16*	1.86
Insiders' Non-Expertise	7.04	7.06	0.63	0.37	1.97	1.21
All Retail Traders	6.61	7.40	-2.09**	-2.17	0.14	0.19

Panel E: Value-Weighted Portfolios, Six-Month Holding Period

	Average Returns (bp/Day)		Annual Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	11.35	3.48	19.31**	2.37	21.06**	2.55
Insiders' Non-Expertise	7.45	4.41	7.25	1.36	8.64	1.63
All Retail Traders	5.89	6.69	-2.22**	-2.17	-0.05	-0.06

Panel F: Equal-Weighted Portfolios, Six-Month Holding Period

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	8.42	4.77	8.45	1.21	10.64	1.54
Insiders' Non-Expertise	6.43	6.07	0.48	0.18	2.29	0.87
All Retail Traders	5.24	6.12	-2.55**	-2.35	-0.46	-0.52

Table A3. Transactions-Based Calendar-Time Portfolios (Cont.)

Panel G: Value-Weighted Portfolios, Three-Month Holding Period

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	13.33	-0.48	30.45***	2.71	33.04***	2.94
Insiders' Non-Expertise	10.03	7.01	8.33	1.13	10.95	1.50
All Retail Traders	5.70	6.71	-2.64*	-1.87	0.04	0.03

Panel H: Equal-Weighted Portfolios, Three-Month Holding Period

	Average Returns (bp/Day)		Annualized Difference		Annualized Alpha	
	Buy	Sell	Mean	*t*-stat	Mean	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise	11.08	1.76	21.89**	2.23	24.50**	2.57
Insiders' Non-Expertise	6.54	7.97	-1.71	-0.46	0.76	0.20
All Retail Traders	5.44	6.45	-2.71**	-2.10	-0.43	-0.39

Table A4. Buy-and-Hold Abnormal Returns, 12 Months

This table shows results analogous to those reported in Table 5, but using a 12-month holding period. A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. All Retail Traders' Trades indicates trades made by the other individuals in the Large Discount Broker (LDB) dataset. We report three-month (63 days) buy-and-hold returns as well as returns in excess of the DGTW benchmark return and the value-weighted industry benchmark returns. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

		Equal Weighted			Trade-Size Weighted		
		Raw	DGTW-Adjusted	Industry-Adjusted	Raw	DGTW-Adjusted	Industry-Adjusted
		(1)	(2)	(3)	(4)	(5)	(6)
Insiders' Expertise Trades (Exp)	Buy	27.92***	7.78	6.55	25.96***	4.46	4.18
		(5.45)	(1.56)	(1.37)	(5.22)	(0.89)	(0.88)
	Sell	16.14***	-1.83	-2.73	13.49***	-4.46	-3.60
		(3.94)	(-0.50)	(-0.77)	(2.90)	(-1.06)	(-0.91)
	Buy - Sell	11.78*	9.61	9.27	12.47*	8.92	7.78
		(1.80)	(1.55)	(1.55)	(1.83)	(1.36)	(1.26)
Insiders' Non-Expertise Trades (Nexp)	Buy	15.53***	-0.97	-4.35***	16.63***	-0.45	-2.05***
		(16.14)	(-1.12)	(-4.89)	(18.62)	(-0.56)	(-2.60)
	Sell	16.81***	-0.89	-2.19**	15.97***	-1.80**	-2.09**
		(14.86)	(-0.87)	(-2.05)	(16.91)	(-2.14)	(-2.44)
	Buy - Sell	-1.28	-0.08	-2.16	0.66	1.35	0.04
		(-0.86)	(-0.06)	(-1.56)	(0.51)	(1.17)	(0.03)
All Retail Traders' Trades (RT)	Buy	15.21***	-1.37***	-2.72***	16.56***	-0.64***	-1.96***
		(265.02)	(-26.98)	(-51.04)	(295.50)	(-12.95)	(-38.23)
	Sell	17.52***	0.19***	-0.81***	18.77***	0.77***	-0.40***
		(288.16)	(3.57)	(-14.30)	(315.07)	(14.69)	(-7.39)
	Buy - Sell	-2.31***	-1.57***	-1.91***	-2.21***	-1.41***	-1.56***
		(-27.59)	(-21.06)	(-24.67)	(-27.02)	(-19.57)	(-20.89)

Table A5. Insider Trades and Local Stocks

A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the 3 digit SIC code definition. Trades in an insider's own firm are excluded, while the remaining insider's trades are defined as Non-Expertise. A stock purchase or sale by a corporate insider is classified as Local if the headquarter of the traded firm is within 250 miles of the headquarter of the insiders' firm(s). In Panel A (Panel B) we report equal-weighted (trade-size-weighted) 3-month buy-and-hold DGTW-adjusted return. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

Panel A: Equal-Weighted Three-Month DGTW-Adjusted Returns

	Local Stocks			Non-Local Stocks		
	All	Expertise	Non-Expertise	All	Expertise	Non-Expertise
	(1)	(2)	(3)	(4)	(5)	(6)
N	1205	179	1026	3619	233	3386
Buy	0.48	-2.03	0.92	-0.09	6.69***	-0.52
	(0.55)	(-0.92)	(0.98)	(-0.19)	(2.83)	(-1.07)
Sell	-1.46	-6.06**	-0.67	0.69	-1.00	0.82
	(-1.58)	(-2.19)	(-0.69)	(1.34)	(-0.50)	(1.52)
Buy - Sell	1.93	4.03	1.59	-0.78	7.69**	-1.34*
	(1.53)	(1.14)	(1.18)	(-1.11)	(2.49)	(-1.85)

Panel B: Trade-Size-Weighted Three-Month DGTW-Adjusted Returns

	Local Stocks			Non-Local Stocks		
	All	Expertise	Non-Expertise	All	Expertise	Non-Expertise
	(1)	(2)	(3)	(4)	(5)	(6)
N	1205	179	1026	3619	233	3386
Buy	3.90***	0.25	4.68***	1.04**	13.04***	0.13
	(4.66)	(0.11)	(5.26)	(2.20)	(5.01)	(0.28)
Sell	0.12	-7.89***	1.47*	-0.68	-4.04*	-0.40
	(0.15)	(-2.85)	(1.93)	(-1.50)	(-1.94)	(-0.88)
Buy - Sell	3.78***	8.14**	3.20***	1.71***	17.09***	0.54
	(3.31)	(2.25)	(2.73)	(2.62)	(5.12)	(0.82)

Table A6. Expertise Trades in Hard-to-Value Stocks, 12-Month DGTW-Adjusted Returns

This table shows results analogous to those reported in Table 6, but using a 12-month holding period. A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. Retail Traders indicates trades made by the other individuals in the Large Discount Broker (LDB) dataset. We sort buy and sell trades into two equally-sized portfolios using the in-sample median value of stock size, residual analyst coverage calculated as in Hong, Lim and Stein (2000), and idiosyncratic volatility calculated in month t-1, following Ang, Hodrick, Xing, and Zhang (2006). The median expertise stock is in the 72nd NYSE-AMEX size percentile. Three-month equal-weighted DGTW-adjusted excess returns are reported. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

Panel A: Expertise Trades and Hard-to-Value Stocks: Size

	Insiders' Trades			Retail Traders	Differences		
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy			
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Firm Size							
Low	12.50	-9.97*	-3.06**	-3.01***	22.47**	15.57*	15.51*
	(1.37)	(-1.81)	(-2.09)	(-35.03)	(2.10)	(1.68)	(1.70)
High	3.02	6.39	1.13	0.26***	-3.37	1.89	2.75
	(0.78)	(1.35)	(1.26)	(4.85)	(-0.55)	(0.47)	(0.71)
Low - High	9.49	-16.36**	-4.19**	-3.28***	25.85**	13.68	12.76
	(0.95)	(-2.25)	(-2.44)	(-32.19)	(2.10)	(1.36)	(1.28)

Panel B: Expertise Trades and Hard-to-Value Stocks: Residual Analyst Coverage

	Insiders' Trades			Retail Traders	Differences		
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy			
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Resid. Analyst Coverage							
Low	17.08**	-2.71	-2.17*	-3.94***	19.79*	19.25**	21.02**
	(2.00)	(-0.49)	(-1.82)	(-58.14)	(1.95)	(2.23)	(2.46)
High	-1.60	-0.95	0.24	1.19***	-0.66	-1.84	-2.79
	(-0.32)	(-0.19)	(0.19)	(15.71)	(-0.09)	(-0.36)	(-0.56)
Low - High	18.68*	-1.76	-2.41	-5.13***	20.45*	21.09**	23.81**
	(1.89)	(-0.24)	(-1.40)	(-50.45)	(1.66)	(2.10)	(2.41)

Table A6. Expertise Trades in Hard-to-Value Stocks, 12-Month DGTW-Adjusted Returns (Cont.)

Panel C: Expertise Trades and Hard-to-Value Stocks: Idiosyncratic Volatility

	Insiders' Trades			Retail Traders	Differences		
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy			
	(1)	(2)	(3)	(4)	(1) - (2)	(1) - (3)	(1) - (4)
Idiosyncratic Volatility							
High	11.30	-10.47*	-4.11***	-2.95***	21.77*	15.40	14.25
	(1.16)	(-1.66)	(-2.79)	(-33.32)	(1.88)	(1.57)	(1.46)
Low	4.43	6.72*	2.17**	0.20***	-2.29	2.25	4.23
	(1.47)	(1.83)	(2.46)	(3.94)	(-0.48)	(0.72)	(1.41)
High - Low	6.87	-17.19**	-6.28***	-3.15***	24.06*	13.15	10.02
	(0.68)	(-2.36)	(-3.66)	(-30.91)	(1.92)	(1.27)	(0.98)

Table A7. Financial Firm Insiders, 12-Month DGTW-Adjusted Returns

This table shows results analogous to those reported in Table 7, but using a 12-month holding period. A stock purchase or sale by a corporate insider is classified as Expertise if the stock's industry is the same as the insider's based on the three-digit SIC code definition. Trades in an insider's own firm are excluded, while the insider's remaining trades are defined as Non-Expertise. Financial Firm Insiders are individuals who are insiders of at least one financial firm or bank, according to the 49 Fama-French industry definition. 23 out of 105 corporate insiders in our sample are classified as Financial Firm Insiders, and they are responsible for roughly 30% of insiders' trades. The remaining insiders are classified as Non-Financial Firm Insiders. Three-month equal-weighted DGTW-adjusted excess returns are reported. Stock returns and trade size are winsorized at the 1% level within each trade category. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5% and 10% is indicated with ***, **, and *, respectively.

	All Insiders	Financial Firms Insiders	Non-Financial Firms Insiders
	(1)	(2)	(3)
N (#insiders)	105	23	82
Expertise Buy	7.78	8.48**	7.17
	(1.56)	(2.56)	(0.81)
Expertise Sell	-1.83	11.25***	-11.79**
	(-0.50)	(2.82)	(-2.12)
Expertise Buy - Sell	9.61	-2.77	18.96*
	(1.55)	(-0.53)	(1.81)
Non-Expertise Buy	-0.97	-0.21	-1.56
	(-1.12)	(-0.17)	(-1.33)
Non-Expertise Sell	-0.89	0.42	-1.71
	(-0.87)	(0.27)	(-1.27)
Non-Expertise Buy - Sell	-0.08	-0.63	0.15
	(-0.06)	(-0.31)	(0.08)