NBER WORKING PAPER SERIES

INDUSTRY FAMILIARITY AND TRADING: EVIDENCE FROM THE PERSONAL PORTFOLIOS OF INDUSTRY INSIDERS

Itzhak Ben-David
Justin Birru
Andrea Rossi

Working Paper 22115
http://www.nber.org/papers/w22115

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2016

Previously circulated as "Trading Skill: Evidence from Trades of Corporate Insiders in Their Personal Portfolios." We benefited from the comments of René Stulz and Michael Weisbach. We thank Terrance Odean for providing the data. The authors appreciate comments received from participants in seminars at Case Western Reserve University, Drexel University, Georgetown University, Ohio University, The Ohio State University, the University of Cincinnati, the University of Illinois, and the U.S. Securities and Exchange Commission. Ben-David and Birru's research was supported by the Dice Center at the Fisher College of Business. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Industry Familiarity and Trading: Evidence from the Personal Portfolios of Industry Insiders
Itzhak Ben-David, Justin Birru, and Andrea Rossi
NBER Working Paper No. 22115
March 2016, Revised December 2016
JEL No. G11,G14

ABSTRACT

We study whether industry familiarity is an advantage in stock trading by exploring the trading patterns of industry insiders in their own personal portfolios. To do so, we identify accounts of industry insiders in a large dataset provided by a retail discount broker. We find that insiders trade firms from their own industry more frequently. Furthermore, they earn abnormal returns exclusively when trading own-industry stocks, especially obscure stocks (small, low analyst coverage, high volatility). In a battery of tests, we find no evidence of the use of private information. The results are most consistent with the interpretation that industry familiarity is an advantage in stock trading.

Itzhak Ben-David
Department of Finance
Fisher College of Business
The Ohio State University
2100 Neil Avenue
Columbus, OH 43210
and NBER
bendavid@fisher.osu.edu

Justin Birru
Department of Finance
Fisher College of Business
The Ohio State University
2100 Neil Avenue
Columbus, OH 43210
birru.2@fisher.osu.edu

Andrea Rossi
Department of Finance
Fisher College of Business
The Ohio State University
2100 Neil Avenue
Columbus, OH 43210
andrearossi832@msn.com

A online appendix is available at http://www.nber.org/data-appendix/w22115

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 the industry in which they are employed, 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 an industry is related to skill.

In this paper, we provide evidence on the ability of investors to capitalize on industry familiarity from a novel source. Specifically, we examine trades made by industry insiders in their own personal portfolios. In this setting, top corporate executives serve as retail traders. Compared with average employees who engage in stock trading (such as those studied in Døskeland and Hvide, 2011), the executives in our study are likely to have a better understanding of their industry. Our tests contrast executives' trading patterns and performance in stocks of firms within their industry with those outside the industry. After documenting that insiders outperform when trading stocks in their own industry, we attempt to identify the type of information on which insiders are trading. To do so, we focus on the specific sources of trading profits that have been documented in prior research, such as trading ahead of earnings announcements or merger and acquisition

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

(M&A) announcements, or trading in conjunction with the trades of firm insiders. Our findings, however, do not reveal any evidence that insider profits in industry stocks originate from any of the commonly identified sources. Instead, our analysis suggests that industry familiarity is the trading advantage that best explains our results.

Our study also contributes to the understanding of trading and portfolio holdings of corporate executives. Past research has shown that insiders can profitably trade 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 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 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 avoiding stocks in their industry of profession. In contrast, our results show that insiders actually trade disproportionally more in own-industry stocks relative to non-own-industry stocks. 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 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 to be correlated with returns on insider human capital, insiders should avoid own-industry stocks unless they possess some advantage in trading these 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 various methods of measurement: 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 purchases minus own-industry sales earns a Carhart alpha of 16% per year. In contrast, a portfolio of non-own-industry purchases 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 purchases within industry outperform other stocks in the same industry, and stock sales within industry underperform other stocks in the same industry. In other words, insiders are able to identify winners and losers in the cross-section of industry stocks.

We next examine the source of superior performance of industry insiders in expertise stocks. One possibility is that insiders are better at deciphering public industry information. An industry insider, for example, might be better than other investors or analysts at understanding the implications of a new product announcement on future earnings. As an alternative to this hypothesis, we test whether the same mechanisms that the past literature finds to be responsible for insider profits can also explain insider outperformance in expertise stocks: for example, trading ahead of merger announcements (e.g., Keown and Pinkerton, 1981) or based on future earnings information (e.g., Beneish, Vargus, 2002, Aboody, Hughes, and Liu, 2005). The hypotheses are, of course, not mutually exclusive.

Our first test suggests that the industry insiders outperform due to an information advantage. In particular, 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.

Next, we conduct several tests that are motivated by information-based sources of insider profits documented in the literature. To directly test whether expertise profits emanate from the same source as insider trading profits we examine the correlation between a company’s insiders and industry insiders in our sample. In fact, we find no evidence for this effect. We further sharpen the test using the Cohen, Malloy, and Pomorski (2012) method of flagging insider trades that are likely to convey information, but again fail to find any significant correlation.

Our second empirical strategy is based on tracking the trades of industry insiders around major news releases. It is possible that industry insiders are privy to certain industry information before it is released to the public, making them likely to trade ahead of the release of that information as news. Thus, we run several tests that are designed to test whether industry insiders trade ahead of specific news events. First, we test whether they trade ahead of earnings announcements by the traded firm, and whether those trades outperform. We find no evidence of that correlation, and trading performance around traded firms' earnings announcements is not of higher quality than other trades.

Third, we hypothesize that industry insiders use news information from their *own* firm to trade other firms in the industry. We test for a correlation between trading activity of industry insiders and their own earnings announcements. We find no association between the returns of their earnings announcement (as a proxy for the surprise) and the propensity to trade another firm in the industry.

Fourth, we examine whether insiders trade ahead of M&A announcements. Many prior studies focus 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; Griffin, Shu, and Topaloglu, 2012; Kedia and Zhou, 2014; Augustin, Brenner, and Subrahmanyam, 2015). We find no evidence that insiders in our sample trade ahead of M&A activity in other firms. For all of these tests, we show that our non-results are robust to defining expertise differently and that our non-results are not driven by low power but rather that the correlation does not exist.

Overall, despite having sufficient statistical power to detect expertise trading ahead of major news events, we find no smoking gun for the alternative hypotheses. Our tests cannot completely rule out informed trading in advance of news events as the source of industry insiders profits. Yet, if trading ahead of news events is responsible for industry insiders' profits, it needs to be orthogonal to the sources investigated here, which are considered the major sources of news in the academic literature: trades by corporate insiders of the traded firm, earnings announcements of the traded firm, earnings announcements by their own firm, and merger announcements.

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. Our results appear to provide little support for other sources of profits.

Our finding that industry experience increases an insider's ability to decipher public information within that industry is consistent with recent evidence that industry expertise matters. Bradley, Gokkaya, and Liu (2015) determine that analyst forecasts are more accurate for firms in industries in which the analyst has previous work experience. In the mutual fund setting, Cici, Gehde-Trapp, Göricke, and Kempf (2014) find evidence that mutual fund managers' trades in industries in which they have previous work experience outperform other trades.

Our analysis also sheds light on the role that expertise plays in the trades of insiders in particular. Alldredge and Cicero (2015) show that insiders often rely on public information about their principal customers to make profitable sales of own-firm stock. Their analysis highlights the ability of insiders to profit on own-firm trades due to their expertise and increased attentiveness to public information relative to outside investors. We document that the trading benefits of insider expertise extend beyond an insider's own firm, as expertise also benefits insiders' retail trades in non-own firm stock within their industry. Thus, our findings also contribute to the open question of retail trader skill. Finding that insiders engage in profitable retail trading for at least a subset of their trades is consistent with the evidence in Kelley and Tetlock (2013) that some retail trades communicate novel cash flow information. The results add to the debate in the literature as to whether retail trades convey new information to the market. Kelley and Tetlock (2013), Kaniel, Saar, and Titman (2008), and Kaniel et al. (2012) provide evidence that retail trades convey valuable information about returns and cash flows, while Dorn, Huberman, and Sengmueller (2008), Odean (1999), Barber and Odean (2000, 2002), Hvidkjaer (2008), Barber, Odean, and Zhu (2009), and Døskeland and Hvide (2011) find no evidence that retail trades move prices closer to their fundamental value. Our analysis reveals that expertise is valuable and can help explain the outperformance of some retail trades.

2 Data and Summary Statistics

2.1 Industry 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 industry 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.

Our main dataset is based on matching these two databases. As a way of illustration, consider the following example. Suppose an insider reports several transactions during the sample period of 1991–1996. The insider trading database reports the name of the firm, the transaction dates, the direction of the trade, and the number of shares traded. We then look for similar transactions in the retail trading database. The trades need to have the same number of shares and dates. Our scoring system, which is detailed in Appendix A, calculates a quality score that allows for small mismatches. For example, some of the trades of an executive may be taking place through another broker's account. Or, the trading dates may be shifted by a day or two relative to the trading database. Additional mismatches may relate to the traded price or consolidating several trades into a single transaction report.

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. By matching individual trades in these two databases, we identify 105 LDB accounts that belong to insiders of publicly traded firms. Appendix A 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 industry 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 files from the Center for Research in Security Prices (CRSP), and accounting data from Compustat. We pull earnings announcement data, including the number of analysts covering each stock, from the Institutional Brokers Estimation System (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.[2]

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 monthly returns are downloaded from Kenneth French's website.[3] The Fama-French industry classifications are sufficiently close to the three-digit SIC code industry definitions 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

[2] The DGTW benchmarks are available at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm
[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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

The majority of results in this study come from comparing the frequency and quality of trades of insiders in stocks within their industry to those outside their industry. We define "expertise trades" in reference to an insider's firm. Stock trades made within the same three-digit SIC industry as the insider's firm are considered expertise trades, and all trades outside of the insider's industry are defined as "non-expertise trades." In the appendix, we show that our results remain qualitatively similar, but decline in magnitude and become noisier, when we use less precise definitions of own-industry 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 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 Trading Expertise Stocks Frequently

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 avoid holding stocks from their own industry unless they have an informational advantage or suffer from a familiarity bias (false belief of having an informational advantage due to familiarity) (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 8.4% 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 4.1% based on the number of expertise stocks relative to the universe of stocks in NYSE, AMEX, and NASDAQ. In other words, if insiders traded all stocks in equal frequency, 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 tilted 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 4.2% percent of the trades of other retail traders (in line with the benchmark of 4.1% 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. We offer alternative weighting in the last two columns of Panel A, where we instead calculate the trading tilt weighting each trader equally. The results also hold with this weighting scheme.

Panel B shows that the trading tilt toward own-industry stocks 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 industry insiders trade stocks in their own industry more frequently. The higher frequency is not due to insiders' industries being skewed toward those in which retail traders trade disproportionately, as we also show that industry insiders in these industries trade more frequently than other retail traders in these same industries. We next examine whether the frequent trading of expertise industries reflects a familiarity bias or whether insiders truly possess greater expertise in these 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 high frequency of trading 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 superior 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 industry 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 indicates 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 this 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. This 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 further explains 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 IA3, Panel A shows that excluding 1991 from the analysis does not change the results. Table IA3 further addresses the concern that there are unequal numbers of stocks in the portfolio across different days. Table IA3, Panel B weights each day by the aggregate dollar value invested in the portfolio on a given day. Table IA3, 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 IA3, 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 industry 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 Table IA5 of 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 more than 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 16.0% 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 3.0% per year.

We perform some robustness tests. Internet Appendix Table IA4, Panel A, shows that the results from equal-weighted portfolios are similar to the value-weighted results reported in Table 4. The rest of Table IA4 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

We also confirm that our results are robust to alternative methods of computing returns. 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 IA1 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 6.0% 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 result 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 results 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 trade using larger sums of money when 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 IA1. Table IA2 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.[4] As Table IA2 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.[5]

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.

We repeat the main tests discussed in Section 4.1 for industry-adjusted returns, and present the results in Columns (3) and (6) of Table IA1. 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.

4.3 Is the Performance Driven by Local Expertise Stocks?

[4] In Table IA2, we assume that the first sale following a purchase of the same stock by the same individual closes the individual's position.

[5] 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 suggests that skill may ameliorate the bias of the disposition effect.

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 IA6 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 IA6 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.

We also investigate the returns of expertise trades in local firms. Table IA6, 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 indicate 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.

4.4 Alternative Industry Definition

In Appendix D, we show that our performance results are robust to alternative definitions of own-industry trades. In particular, we examine seven alternative, less precise, definitions of industry. The looser industry classifications have the advantage of enlarging the sample of expertise trades; however, the cost of the looser industry classifications is that industry is measured with more noise, causing less precision in identifying trades that are likely to be true expertise trades. Appendix Table A1 repeats the analysis of Tables 2 to 5 using the alternative industry definitions. As discussed below, these results are robust to the alternative industry definitions.

Panel A of Table A1 details the number of purchases and sales that are classified as expertise under each of the alternative industry definitions. The sample size of purchases ranges from 214 using the three-digit definition of industry to 688 using the Fama-French 12 industry definition of expertise. As Panel B shows, the conclusion that insiders overweight own-industry trades is robust to all alternative industry definitions. Similarly, Panel C shows that using the metric of holdings-based alphas, insiders exhibit outperformance in their expertise trades under all definitions of industry, although in some cases the outperformance is not statistically significant. Panels D and E show that the outperformance results are also robust to the alternative industry definitions when examining the transactions-based 12-month buy-minus-sell annualized Carhart alphas, and DGTW-adjusted three-month buy-and-hold abnormal returns, respectively. Table A1 shows that the results of Tables 2 to 5 are qualitatively similar, though generally not as strong, when using the alternative industry definitions.

4.5 Frequency of Expertise Trades

The findings presented in Section 4 suggest that corporate insiders' trades in stocks in their own industry are on average profitable. Given this result, it is interesting to know whether some insiders trade expertise stocks more than others and whether trading frequency is related to skill. In Table IA8 of the Internet Appendix we provide concise answers to these questions. Columns (1) to (3) report the 3-month abnormal return results which were discussed in Sections 4.1.3 and 4.3. In Columns (4) to (6) we repeat the same tests after excluding the top 10% of insiders ranked by number of expertise trades executed. The first result in this table is that the number of expertise trades in the latter tests is significantly smaller. In fact, the 10% of insiders that trade expertise stocks the most execute between 40% and 50% of such trades, depending on the industry definition used. Second, the profitability of expertise trades improves after the insiders that trade the most are excluded. Moreover, in an unreported test, we find that there is no significant correlation between the number of expertise trades an insider makes and the average profitability of his/her trades. Therefore, the main findings presented in Section 4 are driven by the bulk of insiders who trade less frequently – most of them trading expertise stocks one to four times over the sample.

5 What Types of Information Are Executives Trading On?

The abnormal performance of within-industry trades of insiders documented in Section 4.1 is consistent with multiple 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 conclude 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.

Alternative explanations for abnormal expertise trades rely on insiders trading ahead of specific news events. If this is the case, expertise trades are profitable, not because insiders possess skill or expertise in deciphering public information, but rather because they are privy to news regarding firms in their industry.

In this section, we conduct several tests that attempt to identify evidence of specific sources of insider expertise profits. To do so, we focus on the most important specific sources of insider profits that have been detected in the literature. Although no variable is likely to be correlated with the entire set of profitable trades, our purpose is to provide several tests that can capture the main sources of profitable insider trading documented in the literature.

5.1 Characteristics of Traded Stocks: Hard-to-Value Stocks

Our first set of tests looks at the characteristics of stocks traded by industry insiders. In particular, we want to determine whether the stocks traded by insiders provide an opportunity to use an informational advantage. 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. Importantly, we note that such an informational advantage could come from public or private sources. Hard-to-value stocks simply have greater information asymmetry. We use three separate measures to characterize hard-to-value stocks, and each suggests that trades in hard-to-value stocks tend to be the most profitable.

We use size, residual analyst coverage, and idiosyncratic volatility as proxies for being 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 5 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 classifies stocks based on idiosyncratic volatility. Each panel displays future returns for expertise buys and sells for 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 12.8% 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 -1.2%) for stocks of above-median size. Panels B and C provide very similar results when classifying stocks based on 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 8.5% 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 10.7% over the following three months, while the difference is a statistically insignificant 1.1% for those stocks with below-median idiosyncratic volatility.

Overall, we find that insiders outperform when trading hard-to-value stocks. These results bolster the previous results about outperformance and suggest that industry insiders exploit some type of information asymmetry when trading stocks in their industry.

5.2 Tests for Trading Ahead of News Events

We next turn to testing specific sources of insider profits that have been detected in the literature. To do so, we isolate instances in which a specific source of insider profits is more likely to be used or is more profitable, and then test whether the executives in our sample are more likely to trade in these circumstances and whether their outperformance is stronger when they do. We conduct several tests that attempt to answer the following questions:

(1) Do some expertise trades coincide with the trades of the firm's insiders?
(2) Is there trading ahead of news?
    a. Trading ahead of earnings announcements of the traded firm
    b. Trading ahead of earnings announcements of own firms
    c. Trading ahead of merger announcements

These tests encompass the settings in which the prior literature documents that profitable insider trading is most likely to occur.

5.2.1 Expertise Trades that Coincide with Trades of the Firm's Insiders

The most general way to test whether expertise profits emanate from the same source as insider trading profits is to test whether the expertise trades are correlated with the trades of insiders. For instance, if an industry insider trades the stock of Firm A at the same time that insiders of Firm A trade their own-firm's stock, then this potentially signals that the expertise profits share a common explanation with insider profits. Our tests use three sets of trades by insiders of the traded firm: (1) all trades, (2) trades of top executives, and (3) trades identified as capturing valuable information based on Cohen, Malloy, and Pomorski (2012).

Table 6 tests the hypothesis that the timing of the trades of industry insiders is correlated with the timing of the trades of insiders of the traded firms. Specifically, we investigate whether expertise buys are disproportionately more likely to occur in conjunction with insider trading buys. We conduct an analogous test for sells. For each expertise trade, we examine the fraction of insider trading over our entire sample period that occurs in a window around the expertise trade. We then average this value across all expertise trades. If expertise trade profits emanate from the same source as the profits of insiders, we would expect to find that a disproportionate amount of insider trading occurs in close proximity to expertise trades with the same sign.

The timing of the trades in this test is important. Industry insiders might pay close attention to the actions of other insiders, in particular to those in their own industry, and they might mimic those trades once they become public. To avoid capturing mimicked trades based on public information, in Table 6 we consider two different windows: the first spanning from one day before to seven days after, and the second spanning from one day before to 15 days after each LDB trade.

In Panel A, we examine whether the expertise and non-expertise trades analyzed in this paper occur in conjunction with the trading of all insiders at the traded firm who filed trades with the SEC. In Panels B and C of Table 6, we posit that some subsamples of insiders might be particularly informative. The results in Panel A fail to provide support for expertise trades occurring in conjunction with insider trades. In Columns (1) to (6), we analyze insider trading purchase ratios. 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. Columns (7) to (12) repeat the same test, but for sale ratios instead of purchase ratios, and they show similar results: expertise sales do not take place in conjunction with insider trading sales.

The trades of high-ranking insiders that oversee the daily activities of a company are likely to be particularly informative about the source of insider trading profits as these insiders have access to more actionable information than the average insider reporting to the SEC. For this reason, in Panel B we examine only the trades of top executives of traded firms.[6] We find that insiders of the traded firm are more likely to buy in conjunction with expertise buys than retail trader buys (Columns (1) and (4)). However, the differences between expertise and retail trades are not statistically significant in one-tailed tests (*p*-values are 0.17 and 0.20, respectively). Insiders are more likely to engage in insider trading purchases around expertise purchases than expertise sales, but again the difference is not statistically significant. The analysis of insider trading sale ratios in Columns (7) to (12) of Panel B reveals no evidence in support of a common component to insider and expertise profits. Insiders are much less likely to engage in insider selling around expertise sales than around non-expertise sales and retail trader sales. Additionally, comparing "buy" and

[6] The results presented are robust to different definitions of top executives, all of which include CEOs, CFOs, and COOs. Under the different definitions, 9.5% to 15% of the insider trades are defined as being made by top executives.

"sell" columns in a given time window, we find that insiders of the traded firms are not more likely to engage in selling around expertise sales than they are around expertise purchases.

To provide assurance that our test has power to identify trades that coincide the trades of insiders, we also report results for non-executive insiders. We expect the trades of non-executive insiders to coincide with those of executive insiders at the same firm. The last row of Panel B shows that this is indeed the case. The purchases of non-executive insiders very strongly coincide with the purchases of executive insiders. Similarly, the timing of sales of non-executive insiders is very highly correlated with the timing of sales of executive insiders.

Cohen, Malloy, and Pomorski (2012) propose a new way to identify the insiders whose trades are likely to contain more valuable information. They analyze the past history of trading at the individual insider level, and they suggest that insiders who have always traded in the same month for the past few years are "routine" insiders and that their trades do not predict future returns. Conversely, the remaining insiders can be defined as "opportunistic." In Panel C, we repeat the test using only the trades of opportunistic insiders[7] to compute the trading ratios. The results in Panel C are similar to those for the executives-only sample in Panel B. We find some weak evidence that insiders are more likely to buy around expertise buys than non-expertise buys or retail buys and that insiders are more likely to buy around expertise buys than expertise sells, though none of the differences are statistically significant. Insider sells are again more likely to occur around expertise buys than expertise sells, inconsistent with expertise sells sharing the same sources of information as insider sells. In the last row, we perform a test to verify the power of the test carried out in this table. In particular, we check whether the test can detect simultaneous trading by opportunistic and non-opportunistic insiders at the same firm. This test is analogous to the one for non-executives in Panel B, and the results again suggest that the average trading ratio test presented in this table has the power to detect simultaneous trading with the same sign when it is taking place.[8]

[7] Cohen, Malloy, and Pomorski (2012) suggest two definitions of "routine," one at the trader level and one at the trade level, and report that both are equally good. To maximize the power in our tests, we count as opportunistic the trades made by opportunistic insiders as well as the non-routine trades made by routine insiders.

[8] Comparing the last row of Panel B with the last row of Panel C in Table 6 reveals that non-executives seem to trade in conjunction with top executives more than non-opportunistic insiders do with opportunistic insiders. This is not surprising because, by virtue of how Cohen, Malloy and Pomorski (2012) define opportunistic and routine insiders, a significant fraction of the trades of any given non-opportunistic insider takes place in the same calendar month of different years, while no such patterns exists for the trades of opportunistic insiders.

The weak evidence of increased insider trading of top executives and opportunistic insiders around expertise buys relative to non-expertise buys and retail buys motivates us to conduct further tests. In Panel D, we examine whether the expertise buys occurring in close proximity to insider buys are contributing to the expertise outperformance results.

The regressions in Panel D include all buy trades in the LDB. The regressions include a dummy for expertise buys and a dummy for non-expertise buys, with retail buys as the omitted group. The baseline results in Column (1) document the earlier results that expertise buys outperform retail trader buys. In this panel, we identify expertise, non-expertise, and retail buys that occur in conjunction with insider trading purchases based on two windows: from $t – 1$ to $t + 7$ and from $t – 1$ to $t + 15$ around the LDB trades. Specifically, for each LBD purchase, we compute an indicator equal to 1 if there was an insider trading purchase in the same stock in the selected window. Columns (2) and (3) focus on trades in conjunction with those of top executives. The first row of coefficients documents that retail buys occurring in conjunction with insider buys outperform; however, the same is not true for expertise buys occurring in conjunction with insider buys. Instead, the coefficients in Columns (2) and (3) for the expertise buy variable interacted with insider trading are negative, suggesting that expertise buys occurring in conjunction with insider buys actually underperform the rest of the expertise buys, though only Column (3) is statistically significant. Columns (4) and (5) use the Cohen, Malloy, and Pomorski (2012) definition of opportunistic insider buys, and the results again show that expertise buys occurring in conjunction with insider buys do not outperform the rest of the expertise buys.

Panel E replicates the analysis in Panel D using sales rather than purchases. The results in Panel E fail to provide evidence that expertise sales occurring in conjunction with insider sales outperform the rest of the expertise sale trades. In conclusion, the analysis focusing on the trading of insiders of other firms fails to turn up any evidence that the profits of expertise trades share a common source with the profits of insider trades.

One concern is that our regression non-result is driven by weak power rather than lack of results. To assess whether this is the case, consider Panels D and E of Table 6. In particular, the coefficient on the interaction between the insider trading dummy and the expertise buy (or sell) has, in most specifications, the opposite sign than is predicted by the hypothesis that expertise trades occur in conjunction with insider trades. Furthermore, the insider expertise buy and sell variables continue to maintain their economic and statistical significance in the presence of the interaction term, indicating that expertise trades that do not occur concurrently with insider trades still deliver large significant outperformance.

Although fully ruling out that expertise and insider trades share a common source is not possible, our results thus far fail to uncover evidence that insiders exploit inside information in their trades. Rather, our findings are most consistent with insiders being able to more efficiently process public information than other traders.

5.2.2 Trading Ahead of Earnings Announcements of the Traded Firm?

Next, we examine whether the profitability of expertise trades results from trading ahead of news. We begin by focusing on trading that occurs immediately in advance of earnings announcements of the traded firm.

Table 7 assesses whether industry insiders outperform in their trades occurring in advance of earnings announcements. Panel A of Table 7 reports the earnings announcement CAR for expertise stocks that are traded in the period prior to an earnings announcement of the traded firm. Three different methodologies are used to classify expertise buys and sells. “All” includes all trades made by an insider. In this case, the same stock can potentially be classified as both a buy and a sell. “Net” classifies a stock as an expertise buy or sell based on the net quantity traded before an earnings announcement. “Last” classifies trades as buys or sells based only on the last transaction occurring in the period leading up to the earnings announcement. Regardless of the classification methodology used, expertise buys exhibit positive but statistically insignificant returns, while expertise sells exhibit negative but statistically insignificant returns. The difference in returns between expertise buys and sells is never significant at the 10% level for trades occurring in the window from (-15, -2) before an earnings announcement. For the window that includes all trades made in the period leading up to an earnings announcement, the difference in returns between expertise buys and sells is significant at the 10% level under the “All” classification methodology, but is not statistically significant using the alternative methodologies. Table 7, Panel A, fails to uncover evidence that the observed outperformance of expertise trades is driven by trading ahead of earnings announcements.

To ensure that these non-results are not due to the tests having weak power, we conduct an additional test. This time, we examine industry insiders' performance after we remove all the trades that take place immediately prior to the traded firms' earnings announcements. If industry insiders' outperformance is driven by trading ahead of the earnings releases of the firms that they trade, removing these trades should reduce the observed outperformance. In fact, when we remove these trades, the performance of industry insiders remains virtually unchanged. The returns that are earned by industry insiders around earnings announcements in expertise trades (buy-minus-sell) is 0.93%, which is about 15% of the three-month adjusted buy-sell DGTW-adjusted returns reported earlier.

Also, in an unreported analysis, we 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 trades of customers or suppliers. These few trades do not substantially contribute to the ability of insiders to outperform on expertise trades.

We also examine the frequency of trades in same-industry firms around the earnings announcements of the traded firms. The analysis is presented in Internet Appendix Figure IA1. The top panel (Figure IA1a) shows the chronological distribution of buy transactions, and the bottom panel (Figure IA1b) presents the chronological distribution of sell transactions. As a benchmark, we include the distribution of trades by insiders in non-expertise stocks as well as the distribution of trades by other retail traders. The charts show that the propensity of industry insiders to trade expertise stocks around earnings announcements is largely in line with the propensity of other traders to trade these stocks and with their own propensity to trade non-expertise stocks.

5.2.3 Trading Ahead of Earnings Announcements of *Own* Firm?

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, 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 7, Panel B, we explore whether insiders' expertise trades potentially reflect trading on insider information regarding their own firm. To test this hypothesis, we examine the profitability of expertise trades that occur in the period immediately preceding the own-firm earnings announcement of the insider. If insiders have 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.

The relationship between own-firm earnings surprises and the future performance of closely related firms is potentially ambiguous. For instance, a positive shock to profitability for one firm in an industry might reflect an industry-wide profitability shock, predicting a positive relationship between own-firm earnings and the future performance of own-industry firms. On the other hand, a positive shock to profitability for one firm could result from taking market share from other industry firms, predicting a negative relationship between own-firm earnings and the future performance of own-industry firms. Our analysis allows us to distinguish either of these possibilities.

Table 7, Panel B, analyzes the expertise trades of insiders in the 15 days prior to an insider's own-firm earnings announcement and in the entire period leading up to an insider's own-firm earnings announcement, and specifically examines the returns accruing to these expertise trades in the days around the earnings announcement of the insider's own firm. If insiders are using information regarding their own firm's earnings announcement to trade profitably in other stocks in the industry, then we would expect to see that expertise buy (sell) transactions occurring in close proximity to own-firm earnings announcements outperform (underperform) in the days around those announcement. Table 7, Panel B, shows that when focusing on stocks purchased and sold prior to an own-firm earnings announcement, the buys do outperform the sells in the three-day period around the announcement, but the outperformance is not statistically significant. The outperformance is insignificant when using either the all-days or 15-day window to define transactions.

As in Section 5.2.2., we are concerned that our test lacks power and therefore returns no significant results. To check whether this is the case, we perform a similar analysis to that we performed in the previous section. Specifically, we measure the performance of industry insiders without the trades that appear just before their own company's earnings announcements. The updated performance results remain virtually the same as before. Another way to see this is to focus on Column (2) of Table 7, Panel B. The expertise buy-minus-sell return of 0.95% is only about 1/7 of the magnitude of the three-month adjusted buy-sell DGTW-adjusted returns that we documented earlier.

A final concern is that a positive own-firm earnings surprise sometimes reflects good news for other industry firms and sometimes reflects bad news, resulting in no abnormal expertise buys or sells on average. We explore this possibility in Internet Appendix Figure IA2 by testing for the presence of abnormal trading in expertise stocks around own-firm earnings announcements. To the extent that own-firm earnings have any implications (positive or negative) for other firms in the industry, we should expect to see an increase in trading in expertise stocks *in advance* of own-firm earnings announcements. Internet Appendix Figure IA2 reveals some patterns; however, these do not seem to be consistent with the own-firm information story. Figure IA2a examines the frequency of expertise purchases relative to non-expertise purchases in five-day increments in the period leading up to and including the announcement, and Figure IA2b shows analogous statistics for sales. In the five-day period leading up to an earnings announcement, non-expertise purchases actually occur with a greater frequency than expertise purchases. The same is true for non-expertise sales relative to expertise sales.

Interestingly, industry insiders make more expertise trades on the day of the earnings announcement (for purchases) and in the following days (for sales). This pattern is consistent with the industry familiarity story. Once earnings are released, industry insiders feel able to process the information and use it to trade other firms. These results show that outperformance in own-industry trades does not appear to stem from industry insiders using information related to own-firm earnings announcements.

5.2.4 Trading Ahead of Merger Announcements?

M&As are major events in a firm's life. These events typically require months of negotiations, and the information about them could potentially leak and be known within the industry. Several papers detect abnormal trading activity in the period leading up to an M&A

announcement and attribute it to 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 earning potentially large returns. 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. 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) to (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, industry insiders do not appear to be more likely to place buy orders ahead of M&As than other retail traders, 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%.

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 M&A information about other firms in their own industry.

5.2.5 Additional Analysis

We provide an additional, albeit weaker, test of the hypothesis that expertise and insider profits emanate from the same source. Of the 105 insiders in our sample, 23 are associated with financial firms. This group is interesting to explore in isolation because these executives potentially possess information about client firms *outside* their industry. In other words, we test whether these insiders in financial firms profitably trade firms that we generally would call non-expertise (firms outside the insiders' industry). 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).

Appendix Table IA9 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 nonfinancial insiders. Second, insiders in financial firms exhibit no outperformance in 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 support the notion that these insiders do not possess unconditional trading skill, but instead are skilled in trading stocks in their specific areas of expertise. Financial firm insiders are an obvious group in which to explore the presence of informed trading because they 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 share a common source with insider profits. The drawback of this test is the small sample size, and the results should be considered with this fact in mind.

5.3 Alternative Industry Definition

Next, we examine whether our conclusions regarding the source of expertise trade profitability are robust to the seven alternative classifications of industry used in Appendix Table A1. Appendix Table A2 repeats the analyses in Tables 6-10 using the alternative industry definitions. As Panel A of Table A2 shows, defining industry according to the alternative classifications enlarges the expertise sample considerably depending on the classification used. For instance, using the Fama-French 12 industry classification enlarges the sample size of expertise trades to 1,277 trades.

Appendix Table A2 shows that the conclusions regarding the source of expertise profits are unchanged when using the larger samples of expertise trades. Panel B of Table A2 shows that when using the larger sample of expertise trades, expertise profitability is again confined to the most hard-to-value stocks, though the differences are not always statistically significant with the looser industry classifications. Panels C and D show that expertise trades still fail to occur in conjunction with the trades of insiders when using the larger samples of expertise trades, and panel E and F show that the expertise trades that happen in conjunction with insider trading at the traded firms do not substantially contribute to the overall good performance of expertise trades. The final three panels of Table A2 replicate the tests of Tables 8, 9, and 10, respectively, using the alternative industry classifications. Panels G and H show that expertise trades ahead of earnings announcements still fail to exhibit outperformance. Finally, Panel I shows that the larger sample of expertise trades still fails to find any evidence of profitable trading in advance of M&A announcements.

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 recently departed employees and shareholders with a large stake in the company.

In unreported analyses, we find that the outperformance of own-industry trades is present for both executives and board members. Perhaps unsurprisingly, executives display slightly better performance than board members, but this difference is not statistically significant. Former or retired employees rarely trade stocks in the industry of their previous employer, and they do not exhibit outperformance on these trades.

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 same-industry 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.

Our analysis finds important differences between the trading ability of insiders outside and within their industry. Outside their industry, insiders are not skilled traders. In contrast, 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.

Our analysis is also relevant to the debate regarding familiarity and trading skill. Our results suggest that familiarity of a high level, for instance, the level of industry familiarity exhibited by insiders, is a source of trading skill. Furthermore, our findings can explain some of the heterogeity in trading skill among retail traders (Kelley and Tetlock, 2013; Kaniel, Saar, and Titman, 2008; and Kaniel et al., 2012).

Finally, our results shed light on the role that expertise plays in the trades of insiders. Alldredge and Cicero (2015) show that expertise and increased attentiveness to public information relative to outside investors allows insiders to make profitable sales of own-firm stock. Our evidence adds to the existing literature on insider trading by showing that industry insiders use their expertise to engage in profitable trading outside their own firm.

An interesting question is whether the documented effect is larger or smaller in recent years than during our sample period of 1991–1996. 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

This appendix shows how we identify the trading accounts that belong to industry insiders. To do so, we follow a three-step procedure to match the trades in the large discount broker (LDB) database with the Security and Exchange Commission (SEC) insider trading filings.

Step 1: Trade-level matches. We start by merging all the LDB common stock trades with the daily file from the Center for Research in Security Prices (CRSP). 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 was 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 criterion 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 coincidentally identical. 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 trades resemble 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 match perfectly 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 her 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 our matching algorithm 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. We allow exceptions to this rule if we believe 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 were 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 reported the precise dates and quantities for all their trades but the reported purchase prices are, sometimes or always, 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 LDB database belong to industry 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 IA3 that the results in Table 3 are robust to excluding 1991. As a further robustness check, Panel B of Table IA3 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. Panel C of that 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 prior 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 industry 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). Because 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 because 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 on 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 five, 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.

Appendix D: Alternative Industry Definitions

In this paper, corporate insiders' trades outside their own firm are defined as expertise if those trades are in other firms in the same three-digit SIC code industry. In Appendix Table A1 and A2, we replicate the core results in the paper using different industry definitions: two-digit SIC code industries and Fama-French 49, 48, 38, 30, 17, and 12 industries. See Sections 4.4 and 5.3 for a discussion of these robustness tests.

Appendix Table A1. Expertise Results with Alternative Industry Definitions

Panel A: Number of Expertise Trades According to Different Industry Definitions

	Number of Expertise Trades							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Purchases	214	285	290	333	453	498	474	688
Sales	199	283	286	317	417	446	400	589

Panel B: Robustness for Table 2 with Alternative Industry Definitions

Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Across Trades, EW	2.05	1.47	1.41	1.65	1.02	1.10	1.00	1.20
Across Trades, VW	2.72	2.14	2.15	2.76	1.70	1.65	1.20	1.75
Across Insiders, EW	3.31	2.24	2.07	2.38	1.53	1.63	1.24	1.56
Across Insiders, VW	3.28	2.40	2.29	2.65	1.93	2.01	1.50	1.93

Panel C: Robustness for Table 3 with Alternative Industry Definitions

	Holdings-Based Alphas (Basis Points per Day)							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Fama-French 3 Factor Model	5.40**	2.47	2.46	3.46	2.75	1.70	5.05**	3.52
	(2.13)	(1.05)	(1.06)	(1.52)	(1.48)	(0.72)	(1.97)	(1.49)
Carhart 4 Factor Model	5.81**	3.07	3.05	4.18*	3.28*	1.98	5.31**	3.66
	(2.24)	(1.27)	(1.28)	(1.80)	(1.68)	(0.81)	(1.99)	(1.50)
HXZ Q-Factor Model	4.90*	3.39	3.35	4.16*	3.26*	1.73	4.60*	3.08
	(1.92)	(1.43)	(1.43)	(1.82)	(1.71)	(0.72)	(1.78)	(1.27)
Fama-French 5 Factor Model	5.19**	2.60	2.60	3.67	2.26	1.60	4.89*	3.77
	(2.00)	(1.10)	(1.11)	(1.61)	(1.23)	(0.68)	(1.89)	(1.55)

Panel D: Robustness for Table 4 with Alternative Industry Definitions

	Transactions-Based 12-Month Buy-Minus-Sell Annualized Carhart Alphas							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Value-Weighted	15.97***	9.93*	10.07*	4.27	4.25	9.08*	9.04	16.13***
	(2.67)	(1.69)	(1.82)	(0.83)	(0.94)	(1.77)	(1.53)	(2.81)
Equal-Weighted	11.02**	7.57*	7.43*	6.87*	6.24*	7.07*	6.63*	6.57*
	(2.26)	(1.86)	(1.87)	(1.78)	(1.88)	(1.75)	(1.67)	(1.96)

Appendix Table A1. Expertise Results with Alternative Industry Definitions (Cont.)

Panel E: Robustness for Table IA1 with Alternative Industry Definitions

	DGTW-Adjusted 3-Month Buy-And-Hold Abnormal Returns							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Buy, EW	2.76*	2.84**	2.66**	2.44**	1.39	1.03	1.76*	1.49*
	(1.66)	(2.12)	(2.01)	(1.99)	(1.39)	(1.07)	(1.85)	(1.83)
Sell, EW	-3.11*	-0.30	-0.47	-2.03*	-1.65	-0.49	0.81	-0.54
	(-1.90)	(-0.22)	(-0.36)	(-1.69)	(-1.64)	(-0.44)	(0.71)	(-0.57)
Buy - Sell, EW	5.87**	3.14*	3.13*	4.47***	3.04**	1.52	0.95	2.03
	(2.52)	(1.67)	(1.68)	(2.60)	(2.14)	(1.03)	(0.64)	(1.62)
Buy, VW	5.52***	3.57***	3.43***	1.86	2.29**	1.85**	3.40***	3.22***
	(3.10)	(2.78)	(2.73)	(1.61)	(2.54)	(2.05)	(3.51)	(3.98)
Sell, VW	-5.99***	-3.62***	-3.53***	-4.26***	-3.71***	-3.24***	-1.93*	-2.59***
	(-3.54)	(-2.75)	(-2.76)	(-3.95)	(-4.12)	(-3.23)	(-1.82)	(-3.07)
Buy - Sell, VW	11.51***	7.18***	6.96***	6.11***	6.00***	5.09***	5.33***	5.81***
	(4.69)	(3.91)	(3.88)	(3.88)	(4.71)	(3.77)	(3.72)	(4.97)

Appendix Table A2. Tables 6, 7, 8, 9, and 10 with Alternative Industry Definitions

Panel A: Number of Expertise Trades According to Different Industry Definitions

	Number of Expertise Trades							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Purchases	214	285	290	333	453	498	474	688
Sales	199	283	286	317	417	446	400	589

Panel B: Robustness for Table 5 with Alternative Industry Definitions

	Expertise Buy-Minus-Sell in Hard-toValue Stocks, DGTW-Adjusted 3 Month Returns							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Small Firm Size	12.82***	7.70**	7.77**	9.81***	6.10**	3.09	1.26	3.14
	(3.17)	(2.37)	(2.42)	(3.37)	(2.45)	(1.22)	(0.48)	(1.47)
Small-Minus-Big Firm Size	13.97***	9.10**	9.24**	10.73***	6.16**	3.09	0.43	2.22
	(3.05)	(2.43)	(2.49)	(3.14)	(2.15)	(1.05)	(0.14)	(0.88)
Low Residual Analyst Coverage	8.51**	4.40	4.29	6.25**	3.20	3.33	3.50*	2.64
	(2.39)	(1.55)	(1.53)	(2.41)	(1.52)	(1.61)	(1.69)	(1.53)
Low-Minus-High Residual	5.31	2.49	2.28	3.60	0.36	3.57	4.91*	1.22
Analyst Coverage	(1.14)	(0.66)	(0.61)	(1.04)	(0.13)	(1.22)	(1.65)	(0.49)
High Idiosyncratic Volatility	10.74***	5.28	5.50*	7.68**	5.09**	2.84	0.87	2.32
	(2.58)	(1.57)	(1.66)	(2.51)	(1.97)	(1.10)	(0.32)	(1.05)
High-Minus-Low Idiosyncratic	9.69**	4.22	4.72	6.42*	4.13	2.58	-0.36	0.59
Volatility	(2.07)	(1.12)	(1.27)	(1.87)	(1.44)	(0.88)	(-0.12)	(0.24)

Panel C: Robustness for Table 6, Panel B, with Alternative Industry Definitions

	p-values for Differences in Average Insider Trading Ratios for Top Executives							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Exp Buy > Exp Sell APR (-1,+7)	0.23	0.24	0.24	0.27	0.25	0.34	0.03	0.38
Exp Buy > Exp Sell APR (-1,+15)	0.13	0.13	0.13	0.20	0.16	0.10	0.04	0.49
Exp Buy > Retail Buy APR (-1,+7)	0.17	0.32	0.33	0.55	0.61	0.80	0.07	0.45
Exp Buy > Retail Buy APR (-1,+15)	0.20	0.27	0.30	0.44	0.27	0.37	0.05	0.32
Exp Sell > Exp Buy ASR (-1,+7)	0.97	0.88	0.88	0.86	0.58	0.85	0.71	0.71
Exp Sell > Exp Buy ASR (-1,+15)	0.69	0.47	0.46	0.59	0.47	0.54	0.58	0.54
Exp Sell > Retail Sell ASR (-1,+7)	1.00	0.89	0.90	0.94	0.69	0.88	0.66	0.83
Exp Sell > Retail Sell ASR (-1,+15)	0.73	0.49	0.51	0.73	0.70	0.52	0.81	0.69

Panel D: Robustness for Table 6, Panel C with Alternative Industry Definitions

	p-values for Differences in Average Insider Trading Ratios for Opportunistic Insiders							
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Exp Buy > Exp Sell APR (-1,+7)	0.15	0.14	0.14	0.18	0.41	0.15	0.39	0.21
Exp Buy > Exp Sell APR (-1,+15)	0.33	0.38	0.37	0.50	0.60	0.14	0.63	0.32
Exp Buy > Retail Buy APR (-1,+7)	0.28	0.33	0.34	0.44	0.49	0.28	0.24	0.27
Exp Buy > Retail Buy APR (-1,+15)	0.32	0.51	0.53	0.46	0.43	0.22	0.40	0.35
Exp Sell > Exp Buy ASR (-1,+7)	0.75	0.76	0.75	0.57	0.42	0.78	0.38	0.37
Exp Sell > Exp Buy ASR (-1,+15)	0.81	0.82	0.82	0.64	0.48	0.89	0.80	0.50
Exp Sell > Retail Sell ASR (-1,+7)	0.18	0.26	0.27	0.11	0.15	0.37	0.25	0.29
Exp Sell > Retail Sell ASR (-1,+15)	0.24	0.48	0.49	0.20	0.36	0.72	0.58	0.46

Appendix Table A2. Tables 6, 7, 8, 9 and 10 with Alternative Industry Definitions (Cont.)

Panel E: Robustness for Table 6, Panel D with Alternative Industry Definitions

Coefficient for I(there was insider trading buying in window)*Insiders' Expertise Buy								
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Top Executives (-1,+7)	-2.48	-2.67	-2.48	-2.13	-2.52	0.65	-2.41	1.30
	(-0.86)	(-0.99)	(-0.92)	(-0.80)	(-0.95)	(0.17)	(-0.69)	(0.49)
Top Executives (-1,+15)	-4.98*	-5.54**	-5.34**	0.69	1.12	1.56	1.30	2.21
	(-1.68)	(-2.06)	(-2.00)	(0.15)	(0.30)	(0.36)	(0.39)	(0.70)
Opportunistic (-1,+7)	0.60	0.55	0.74	-0.30	-0.43	0.42	-0.90	-0.64
	(0.21)	(0.23)	(0.31)	(-0.12)	(-0.19)	(0.12)	(-0.29)	(-0.22)
Opportunistic (-1,+15)	-1.07	-0.63	-0.44	-1.44	-0.79	0.12	-0.07	0.35
	(-0.36)	(-0.26)	(-0.18)	(-0.62)	(-0.37)	(0.04)	(-0.03)	(0.14)

Panel F: Robustness for Table 6, Panel E, with Alternative Industry Definitions

Coefficient for I(there was insider trading buying in window)*Insiders' Expertise Sell								
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
Top Executives (-1,+7)	1.05	0.80	0.97	2.42	2.85	0.25	0.07	2.90
	(0.12)	(0.16)	(0.19)	(0.40)	(0.72)	(0.07)	(0.02)	(0.77)
Top Executives (-1,+15)	10.87	5.61	5.78	8.08	6.45	1.51	2.33	3.92
	(1.54)	(1.15)	(1.19)	(1.46)	(1.54)	(0.36)	(0.55)	(1.04)
Opportunistic (-1,+7)	2.85	0.32	0.51	1.68	2.81	-0.72	-0.08	3.24
	(0.61)	(0.08)	(0.13)	(0.42)	(0.90)	(-0.23)	(-0.02)	(0.95)
Opportunistic (-1,+15)	6.09	2.14	2.33	4.06	4.06	-0.67	-0.44	2.37
	(1.56)	(0.66)	(0.72)	(1.25)	(1.57)	(-0.24)	(-0.15)	(0.90)

Panel G: Robustness for Table 7, Panel A, with Alternative Industry Definitions

Buy-Minus-Sell CAR(-1,+1) around Traded Stocks Earnings Announcements								
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
All, Up to t-2	1.51**	1.36*	1.30*	1.49**	1.13**	0.33	0.19	0.06
	(1.97)	(1.82)	(1.78)	(2.38)	(2.07)	(0.55)	(0.34)	(0.12)
All, (-15,-2)	0.93	0.79	0.29	1.55	0.97	0.00	-0.34	0.21
	(0.47)	(0.42)	(0.16)	(1.00)	(0.71)	(-0.00)	(-0.23)	(0.15)
Net, Up to t-2	1.47	1.20	1.11	1.29	0.81	0.74	0.42	0.27
	(1.45)	(1.21)	(1.16)	(1.57)	(1.18)	(0.99)	(0.58)	(0.43)
Net, (-15,-2)	0.34	0.24	-0.15	0.70	-0.30	-1.09	-0.66	-0.86
	(0.13)	(0.10)	(-0.06)	(0.39)	(-0.20)	(-0.60)	(-0.37)	(-0.55)
Last, Up to t-2	1.07	0.91	0.81	1.13	0.83	0.72	0.30	0.21
	(1.11)	(0.97)	(0.89)	(1.44)	(1.25)	(1.01)	(0.42)	(0.36)
Last, (-15,-2)	1.01	0.88	0.37	1.17	0.66	0.00	-0.43	-0.07
	(0.49)	(0.45)	(0.20)	(0.75)	(0.48)	(-0.00)	(-0.29)	(-0.05)

Appendix Table A2. Tables 6, 7, 8, 9 and 10 with Alternative Industry Definitions (Cont.)

Panel H: Robustness for Table 7, Panel B, with Alternative Industry Definitions

Buy-Minus-Sell CAR(-1,+1) around Own-Firm Earnings Announcements After Expertise Trades								
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
All, Up to t-2	0.69	0.11	0.19	0.56	0.35	0.01	-0.43	-0.04
	(1.31)	(0.23)	(0.39)	(1.28)	(0.89)	(0.03)	(-1.23)	(-0.13)
All, (-15,-2)	0.95	-0.47	-0.15	0.95	0.15	-1.35	-1.03	0.14
	(0.73)	(-0.25)	(-0.08)	(0.58)	(0.10)	(-0.92)	(-0.83)	(0.14)
Net, Up to t-2	0.86	-0.05	0.06	0.57	0.14	-0.41	-1.04**	-0.45
	(1.02)	(-0.06)	(0.09)	(0.93)	(0.27)	(-0.77)	(-2.10)	(-1.03)
Net, (-15,-2)	1.77	-0.79	-0.46	0.44	-0.61	-1.54	-1.37	0.19
	(1.21)	(-0.35)	(-0.20)	(0.23)	(-0.35)	(-0.91)	(-0.98)	(0.17)
Last, Up to t-2	0.95	-0.22	-0.13	0.31	-0.07	-0.47	-0.77*	-0.24
	(1.23)	(-0.33)	(-0.20)	(0.53)	(-0.15)	(-0.95)	(-1.70)	(-0.60)
Last, (-15,-2)	1.57	-0.72	-0.39	0.48	-0.56	-1.48	-1.33	0.22
	(1.08)	(-0.32)	(-0.17)	(0.25)	(-0.33)	(-0.88)	(-0.96)	(0.20)

Panel I: Robustness for Table 8 with Alternative Industry Definitions

# Insiders' Expertise Trades in Window Before M&A Announcements								
Expertise definition:	3 Digit SIC	49 FF	48 FF	2 Digit SIC	38 FF	30 FF	17 FF	12 FF
(-30,-16)	0	0	0	0	0	0	0	0
(-15,-6)	1	1	1	1	1	1	1	1
(-5,-1)	0	0	0	0	0	1	0	1

References

Aboody, David, John Hughes, and Jing Liu, 2005, Earnings Quality, Insider Trading, and Cost of Capital, *Journal of Accounting Research* 43, 651–673.

Acharya, Viral, and Timothy C. Johnson, 2007, Insider Trading in Credit Derivatives, *Journal of Financial Economics* 84, 110–141.

Acharya, Viral, and Timothy C. Johnson, 2010, More Insiders, More Insider Trading: Evidence from Private Equity Buyouts, *Journal of Financial Economics* 98, 500–523.

Alldredge, Dallin M., and David C. Cicero, 2015, Attentive Insider Trading, *Journal of Financial Economics* 115, 84–101.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259–299.

Augustin, Patrick, Menachem Brenner, and Marti G. Subrahmanyam, 2015, Informed Options Trading Prior to M&A Announcements: Insider Trading? Working Paper.

Barber, Brad M., and John D. Lyon, 1997, Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics, *Journal of Financial Economics* 43, 341–372.

Barber, Brad M., and Terrance Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773–806.

Barber, Brad M., and Terrance Odean, 2002, Online Investors: Do the Slow Die First?, *Review of Financial Studies* 15, 455-487.

Barber, Brad M., and Terrance Odean, 2011, The Behavior of Individual Investors. In G. Constantinides, M. Harris, and R. Stulz (eds.), *Handbook of the Economics of Finance*. Amsterdam: Elsevier.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do Retail Traders Move Markets?, *Review of Financial Studies* 22, 151-186.

Ben-David, Itzhak, and Darren Roulstone, 2012, Corporate Transactions and Limits-to-Arbitrage, The Ohio State University, Working Paper.

Beneish, Messod D., and Mark E. Vargus, 2002, Insider Trading, Earnings Quality, and Accrual Mispricing, *Accounting Review* 77(4), 755–791.

Bodnaruk, Andriy, Massimo Massa, and Andrei Simonov, 2009, Investment Banks as Insiders and the Market for Corporate Control, *Review of Financial Studies* 22, 4989–5026.

Bradley, Daniel, Sinan Gokkaya, and Xi Liu, 2015, Before an Analyst Becomes an Analyst: Does Industry Expertise Matter? *Journal of Finance*, Forthcoming.

Cao, Charles, Zhiwu Chen, and John M. Griffin, 2005, Informational Content of Option Volume Prior to Takeovers, *Journal of Business* 78, 1073–1109.

Carhart, Mark, 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

Cici, Gjergji, Monika Gehde-Trapp, Marc-André Göricke, and Alexander Kempf, 2014, What They Did in Their Previous Lives: The Investment Value of Mutual Fund Managers' Experience Outside the Financial Sector, Working Paper.

Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, 2012, Decoding Inside Information, *Journal of Finance* 67(3), 1009–1043.

Cohen, Randolph B., Christopher Polk, and Bernhard Silli, 2010, Best Ideas, Working Paper.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The Geography of Investment: Informed Trading and Asset Prices, *Journal of Political Economy* 109, 811–841.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035–1058.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2013, Correlated Trading and Returns, *Journal of Finance* 63, 885-920.

Døskeland, Trond M., and Hans K. Hvide, 2011, Do Individual Investors Have Asymmetric Information Based on Work Experience? *Journal of Finance* 66(3), 1011–1041.

Fama, Eugene F., 1998, Market Efficiency, Long-Term Returns, and Behavioral Finance, *Journal of Financial Economics* 49, 283-306.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33(1), 3–56.

Fama, Eugene F., and Kenneth R. French, 2015, A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1-22.

Griffin, John M., Tao Shu, and Selim Topaloglu, 2012, Examining the Dark Side of Financial Markets: Do Institutions Trade on Information from Investment Bank Connections? *Review of Financial Studies* 25, 2155–2188.

Hong, Harrison, Terry Lim, and Jeremy C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *Journal of Finance* 55(1), 265–295.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting Anomalies: An Investment Approach, *Review of Financial Studies* 28, 650–705.

Hvidkjaer, Søren, 2008, Small Trades and the Cross-Section of Stock Returns, *Review of Financial Studies* 21, 1125-1151.

Ivashina, Victoria, and Zheng Sun, 2011, Institutional Stock Trading on Loan Market Information, *Journal of Financial Economics* 100, 284–303.

Ivkovic, Zoran, Clemens Sialm, and Scott Weisbenner, 2008, Portfolio Concentration and the Performance of Individual Investors, *Journal of Financial and Quantitative Analysis* 43(3), 613–656.

Ivkovic, Zoran, and Scott Weisbenner, 2005, Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments, *Journal of Finance* 60, 267-306.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the Industry Concentration of Actively Managed Equity Mutual Funds, *Journal of Finance* 60(4), 1983–2011.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Individual Investor Trading and Return Patterns around Earnings Announcements, *Journal of Finance* 67, 639-680.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual Investor Trading and Stock Returns, *Journal of Finance* 63, 273-310.

Kedia, Simi, and Xing Zhou, 2014, Informed Trading around Acquisitions: Evidence from Corporate Bonds, *Journal of Financial Markets* 18, 182–205.

Kelley, Eric K., and Paul C. Tetlock, 2013, How Wise Are Crowds? Insights from Retail Orders and Stock Returns, *Journal of Finance* 68, 1229-1265.

Kempf, Elisabeth, Alberto Manconi, and Oliver Spalt, 2014, Learning by Doing: The Value of Experience and the Origins of Skill for Mutual Fund Managers, Working Paper.

Keown, Arthur J., and John M. Pinkerton, 1981, Merger Announcements and Insider Trading Activity: An Empirical Investigation, *Journal of Finance* 36(4), 855–869.

Kumar, Alok, 2009, Hard-to-Value Stocks, Behavioral Biases, and Informed Trading, *Journal of Financial and Quantitative Analysis* 44(6), 1375–1401.

Lakonishok, Josef, and Inmoo Lee, 2001, Are Insiders' Trades More Informative? *Review of Financial Studies* 14(1), 79–111.

Massa, Massimo, and Zahid Rehman, 2008, Information Flows within Financial Conglomerates: Evidence from the Banks-Mutual Funds Relation, *Journal of Financial Economics* 89, 288–306.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song, 2011, Do Hedge Funds Trade on Private Information? Evidence from Syndicated Lending and Short-Selling, *Journal of Financial Economics* 99, 477–499.

Mitchell, Mark L., and Erik Stafford, 2000, Managerial Decisions and Long-Term Stock Price Performance, *Journal of Business* 73, 287–329.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55(3) 703–708.

Odean, Terrance, 1999, Do Investors Trade Too Much? *American Economic Review* 89, 1279–1298.

Pomorski, Lukasz, 2009, Acting on the Most Valuable Information: “Best Idea” Trades of Mutual Fund Managers, Working Paper.

Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2012, No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice, *Review of Financial Studies* 25(8), 2563–2599.

Seasholes, Mark S., and Ning Zhu, 2010, Individual Investors and Local Bias, *Journal of Finance* 65(5), 1987–2010.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by Trading, *Review of Financial Studies* 23, 705–839.

Seyhun, H. Nejat, 1998, *Investment Intelligence from Insider Trading* (MIT Press: Cambridge, MA).

Tookes, Heather, 2008, Information, Trading, and Product Market Interactions: Cross-Sectional Implications of Informed Trading, *Journal of Finance* 63(1), 379–413.

White, Halbert, 1980, A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica* 48(4), 817–838.

Zhang, X. Frank, 2006, Information Uncertainty and Stock Returns, *Journal of Finance* 61(1), 105–136.

Figure 1. Characteristics-Adjusted Returns – Buys

This figure shows event-time buy-and-hold DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) for portfolios mimicking the purchases of industry insiders and other retail traders in the large discount broker (LDB) dataset for 63 trading days after portfolio formation. Portfolio positions are trade size–weighted and not rebalanced over time. Trade categories are defined in Table 3.

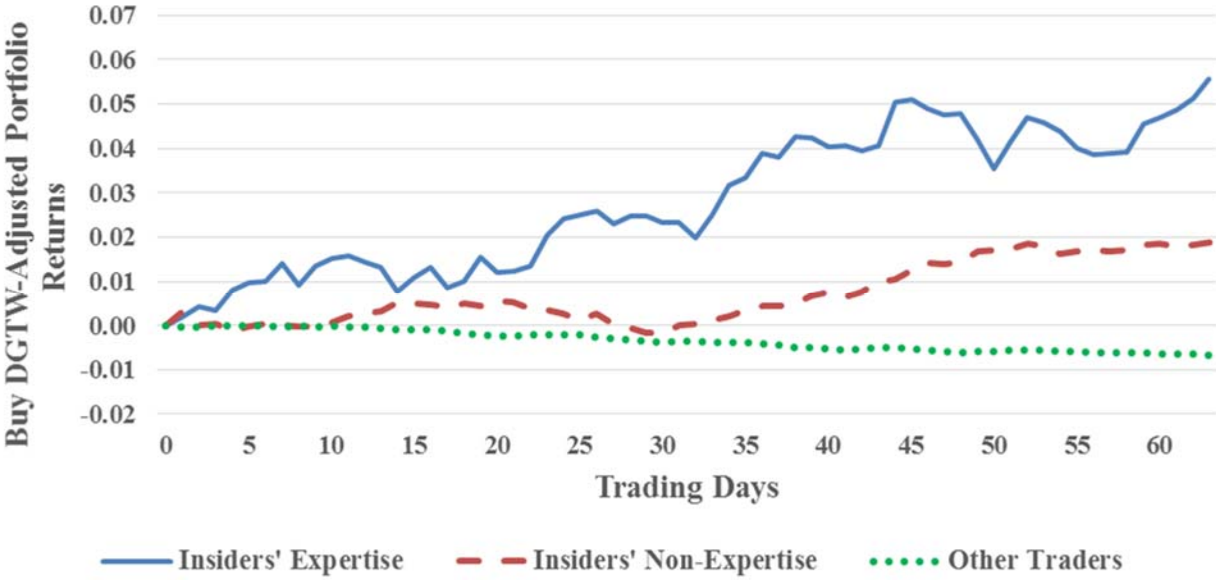

Figure 2. Buy-Minus-Sell Portfolios

This figure shows event-time DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers, 1997) return differences between buy and sell portfolios mimicking purchases and sales of industry insiders and other retail traders in the large discount broker (LDB) dataset for 63 trading days after portfolio formation. Portfolio positions are trade size–weighted and not rebalanced over time. Trade categories are defined in Table 3.

Table 1. Summary Statistics

This table presents summary statistics for the individuals in our sample of 105 industry 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 industry 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 industry 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 one 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

	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 ($)

	N	Mean	Std. Dev.	Min	5%	25%	50%	75%	95%	Max
Size of Insiders' Trades in Own Firm ($)	785	61,374	197,594	109	1,563	5,625	11,500	35,000	228,373	2,498,438
Size of Insiders' Expertise Trades ($)	416	27,656	76,535	156	1,475	4,528	9,550	24,225	91,000	823,975
Size of Insiders' Non-Expertise Trades ($)	4,258	20,979	65,384	100	1,625	4,250	7,684	17,000	61,500	1,499,595
Size of All Other Retail Traders ($)	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 industry 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 large discount broker (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: Trading Tilt Toward Expertise Stocks (Trades Are Equal-Weighted)

	Averaged across Trades		Averaged across Industry Insiders	
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: Trading Tilt Toward Expertise Stocks (Trades Are Dollar-Weighted)

	Averaged across Trades		Averaged across Industry Insiders	
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, and 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. 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% level 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 on that specific day. Within day, trades are value-weighted. Annualized Difference is the annualized average buy-minus-sell portfolio return. Annualized 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. Statistical significance at the 1%, 5% and 10% level is indicated with ***, **, and *, respectively.

	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

Table 5. 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, and 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 (Daniel, Grinblatt, Titman, and Wermers, 1997) 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% level 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							
Small	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)
Big	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)
Small - Big	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	Differences		
	Exp Buy	Exp Sell	Non-Exp Buy	Retail Buy			
	(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 5. 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 6. 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, and the remaining trades are classified as Non-Expertise. Other Retail Traders indicates trades made by other individuals in the large discount broker (LDB) dataset. 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 a window. We consider windows from 1 day before to 7 days after, and from 1 day before to 15 days after the date of each Expertise trade, Non-Expertise trade, or Other Retail Traders trade. To calculate the trading ratios, in Panel A we use the trades of all insiders in the SEC filings, in Panel B we use only the trades of top executives, and in Panel C we use only the trades of opportunistic insiders defined as in Cohen, Malloy, and Pomorski (2012). We also present *p*-values for one-sided tests for differences in means. To verify that the test can identify simultaneous trading when it is likely to be taking place, in Panel B (Panel C) we also report the trading ratios for lower-level, non-executive insiders (for non-opportunistic insiders). In Panel D (Panel E), we regress three-month DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) to buy (sell) trades made by retail traders and industry insiders in the LDB dataset on indicators for the Expertise and Non-Expertise trades and on their interaction with an indicator of whether there was an insider trade with the same sign in the underlying stock. In Panels D and E, returns are winsorized at the 1% level. *t*-statistics based on White (1980) heteroscedasticity-consistent standard errors are in parentheses. Statistical significance at the 1%, 5% and 10% level is indicated with ***, **, and *, respectively. See the text for further details.

Panel A: Average Insider Trading Ratio (%) for All Insiders

	Average Purchase Ratio (APR) (%)						Average Sale Ratio (ASR) (%)					
Window around trades:	(-1,+7)			(-1,+15)			(-1,+7)			(-1,+15)		
	Buy	Sell	*p*-value Buy>Sell	Buy	Sell	*p*-value Buy>Sell	Buy	Sell	*p*-value Sell>Buy	Buy	Sell	*p*-value Sell>Buy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Insiders' Expertise	0.38	0.35	0.40	0.86	0.77	0.35	0.69	0.42	0.94	0.99	0.75	0.86
Insiders' Non-Expertise	0.51	0.45	0.16	0.96	0.80	0.05	0.63	0.52	0.91	1.11	0.95	0.91
Other Retail Traders	0.46	0.42	0.00	0.83	0.77	0.00	0.49	0.52	0.00	0.87	0.91	0.00

p-value Exp Buy APR > Retail Buy APR (-1,+7): 0.75 — *p*-value Exp Sell ASR > Retail Sell ASR (-1,+7): 0.81

p-value Exp Buy APR > Retail Buy APR (-1,+15): 0.44 — *p*-value Exp Sell ASR > Retail Sell ASR (-1,+15): 0.85

Panel B: Average Insider Trading Ratio (%) for Top Executives

	Average Purchase Ratio (APR) (%)						Average Sale Ratio (ASR) (%)					
Window around trades:	(-1,+7)			(-1,+15)			(-1,+7)			(-1,+15)		
	Buy	Sell	*p*-value Buy>Sell	Buy	Sell	*p*-value Buy>Sell	Buy	Sell	*p*-value Sell>Buy	Buy	Sell	*p*-value Sell>Buy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Insiders' Expertise	0.45	0.27	0.23	0.72	0.41	0.13	0.58	0.07	0.97	0.68	0.51	0.69
Insiders' Non-Expertise	0.30	0.23	0.15	0.60	0.59	0.47	0.27	0.30	0.33	0.62	0.59	0.59
Other Retail Traders	0.30	0.28	0.00	0.55	0.52	0.00	0.32	0.36	0.00	0.59	0.63	0.00
Same Firm Non-Executives	1.58	0.13	0.00	1.74	0.22	0.00	0.11	0.79	0.00	0.18	1.08	0.00

p-value Exp Buy APR > Retail Buy APR (-1,+7): 0.17 — *p*-value Exp Sell ASR > Retail Sell ASR (-1,+7): 1.00

p-value Exp Buy APR > Retail Buy APR (-1,+15): 0.20 — *p*-value Exp Sell ASR > Retail Sell ASR (-1,+15): 0.73

Table 6. Trading in Conjunction with Other Firms' Insiders? (Cont.)

Panel C: Average Insider Trading Ratio (%) for Opportunistic Trades (Cohen, Malloy, and Pomorski, 2012)

	Average Purchase Ratio (APR) (%)						Average Sale Ratio (ASR) (%)					
Window around trades:	(-1,+7)			(-1,+15)			(-1,+7)			(-1,+15)		
	Buy	Sell	*p* -value Buy>Sell	Buy	Sell	*p* -value Buy>Sell	Buy	Sell	*p* -value Sell>Buy	Buy	Sell	*p* -value Sell>Buy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Insiders' Expertise	0.51	0.26	0.15	0.83	0.69	0.33	0.88	0.67	0.75	1.35	1.00	0.81
Insiders' Non-Expertise	0.38	0.38	0.48	0.72	0.69	0.41	0.51	0.44	0.83	0.90	0.88	0.57
Other Retail Traders	0.39	0.34	0.00	0.71	0.63	0.00	0.42	0.47	0.00	0.73	0.82	0.00
Same Firm Non-Opportunitic	1.15	0.09	0.00	1.31	0.15	0.00	0.17	0.65	0.00	0.30	0.93	0.00

p -value Exp Buy APR > Retail Buy APR (-1,+7): 0.28 | *p* -value Exp Sell ASR > Retail Sell ASR (-1,+7): 0.18

p -value Exp Buy APR > Retail Buy APR (-1,+15): 0.32 | *p* -value Exp Sell ASR > Retail Sell ASR (-1,+15): 0.24

Panel D: Returns to Buying in Conjunction with Insider Trading

Dependent variable:	3 Month DGTW-Adj. Returns to Buy Trades				
Trading in conjunction with:	n.a.	Top Executives		Opportunistic Insiders	
	(1)	(2)	(3)	(4)	(5)
I(there was insider trading buying in window)					
× Buy		1.65***	1.93***	1.08***	0.90***
		(13.30)	(20.40)	(12.12)	(12.98)
× Insiders' Expertise Buy		-2.48	-4.98*	0.60	-1.07
		(-0.86)	(-1.68)	(0.21)	(-0.36)
× Insiders' Non-Expertise Buy		-0.36	1.82	-1.49	-0.97
		(-0.14)	(0.93)	(-0.81)	(-0.72)
Insiders' Expertise Buy	3.49**	3.57**	3.79**	3.43*	3.57**
	(2.10)	(2.06)	(2.14)	(1.95)	(1.99)
Insiders' Non-Expertise Buy	0.53	0.54	0.44	0.59	0.60
	(1.21)	(1.23)	(1.00)	(1.32)	(1.31)
Intercept	-0.72***	-0.76***	-0.81***	-0.77***	-0.79***
	(-30.13)	(-31.32)	(-32.70)	(-31.08)	(-31.11)
Window Around Trades	n.a.	(-1,+7)	(-1,+15)	(-1,+7)	(-1,+15)
Obs	755016	755016	755016	755016	755016
Adj. R^2	0.00	0.00	0.00	0.00	0.00

Table 6. Trading in Conjunction with Other Firms' Insiders? (Cont.)

Panel E: Returns to Selling in Conjunction with Insider Trading

Dependent variable:	3 Month DGTW-Adj. Returns to Sell Trades				
Trading in conjunction with:	n.a.	Top Executives		Opportunistic Insiders	
	(1)	(2)	(3)	(4)	(5)
I(there was insider trading selling in window)					
× Sell		0.01	0.26**	-0.15*	-0.12
		(0.09)	(2.27)	(-1.72)	(-1.63)
× Insiders' Expertise Sell		1.05	10.87	2.85	6.09
		(0.12)	(1.54)	(0.61)	(1.56)
× Insiders' Non-Expertise Sell		0.64	-0.70	-0.72	-0.50
		(0.28)	(-0.37)	(-0.41)	(-0.37)
Insiders' Expertise Sell	-2.99*	-3.01*	-3.54**	-3.23*	-3.81**
	(-1.83)	(-1.82)	(-2.12)	(-1.86)	(-2.12)
Insiders' Non-Expertise Sell	0.58	0.56	0.61	0.63	0.63
	(1.23)	(1.17)	(1.26)	(1.29)	(1.26)
Intercept	-0.12***	-0.12***	-0.13***	-0.11***	-0.10***
	(-4.68)	(-4.62)	(-5.00)	(-4.02)	(-3.85)
Window Around Trades	n.a.	(-1,+7)	(-1,+15)	(-1,+7)	(-1,+15)
Obs	646933	646933	646933	646933	646933
Adj. R^2	0.00	0.00	0.00	0.00	0.00

Table 7. Returns to Trading Ahead of 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. In Panel A, we test whether the returns to expertise trades are disproportionally earned around the traded firms' earnings announcements. For each expertise trade, we identify the closest subsequent earnings announcement and calculate the cumulative abnormal return (CAR) over the market from one day before to one day after the announcement. In Columns (1), (3), and (5) we include all trades that took place up to two days before the next earnings announcement (essentially the whole sample of trades), and in Columns (2), (4), and (6) we include only trades that took place from 15 days to two days before the next earnings announcement. In Columns (1) and (2) we include all expertise trades meeting the above requirements. In Columns (3) to (6) we adjust for the cases in which an insider makes more than one trade (of any sign) in the same stock before a given earnings announcement. In Columns (3) and (4) the trades are considered as a single purchase (sale) if the net quantity traded before a given earnings announcement is positive (negative). In Columns (5) and (6) the trades are considered as a single purchase (sale) if the last trade preceding the earnings announcement is a purchase (sale). In Panel B, we test whether industry 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. For each expertise trade made by an insider in the sample, we identify the closest subsequent earnings announcement of that insider's firm (in the same industry) and calculate the cumulative abnormal return (CAR) over the market earned by the traded stock from one day before to one day after the announcement of the insider's firm. Columns organization in Panel B is the same as in Panel A. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated with ***, **, and *, respectively.

Panel A: Earnings Announcements of Traded Stocks

CAR(-1,+1) around Earnings Announcements of Traded Stocks						
Consolidation rule	All		Net		Last	
Window before announcement	Up to t-2	(-15,-2)	Up to t-2	(-15,-2)	Up to t-2	(-15,-2)
	(1)	(2)	(3)	(4)	(5)	(6)
CAR of Traded Stock						
Expertise Buy	0.88*	-1.15	0.57	-0.78	0.67	-0.81
	(1.66)	(-1.04)	(0.79)	(-0.67)	(0.98)	(-0.71)
Expertise Sell	-0.63	-2.08	-0.90	-1.12	-0.39	-1.81
	(-1.13)	(-1.26)	(-1.25)	(-0.49)	(-0.59)	(-1.06)
Expertise Buy-Sell	1.51**	0.93	1.47	0.34	1.07	1.01
	(1.97)	(0.47)	(1.45)	(0.13)	(1.11)	(0.49)

Panel B: Earnings Announcements of Own Firm

CAR(-1,+1) Around Own-Firm Earnings Announcement After Expertise Trades						
Consolidation rule	All		Net		Last	
Window before announcement	Up to t-2	(-15,-2)	Up to t-2	(-15,-2)	Up to t-2	(-15,-2)
	(1)	(2)	(3)	(4)	(5)	(6)
CAR of Traded Stocks						
Expertise Buy	0.54	0.64	0.60	1.72	0.65	1.38
	(1.33)	(0.60)	(0.85)	(1.37)	(0.97)	(1.11)
Expertise Sell	-0.15	-0.30	-0.26	-0.05	-0.30	-0.18
	(-0.44)	(-0.41)	(-0.56)	(-0.07)	(-0.78)	(-0.25)
Expertise Buy-Sell	0.69	0.95	0.86	1.77	0.95	1.57
	(1.31)	(0.73)	(1.02)	(1.21)	(1.23)	(1.08)

Table 8. Insiders' Trades around M&A 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, and the remaining trades are classified as Non-Expertise. Retail Traders' Trades indicates trades made by other individuals in the large discount broker (LDB) dataset. In this table, we analyze whether industry insiders tend to trade ahead of mergers and acquisitions (M&As) 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 one to five, six 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 M&A announcements from 1991 to 1996 are from the 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 News with Abnormal Returns > 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 News with Abnormal Returns > 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

Internet Appendix

for

Industry Familiarity and Trading: Evidence from the Personal Portfolios of Industry Insiders

Itzhak Ben-David

Fisher College of Business, The Ohio State University, and NBER

Justin Birru

Fisher College of Business, The Ohio State University

Andrea Rossi

Fisher College of Business, The Ohio State University

Table IA1. Buy-and-Hold Abnormal Returns, Three 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, and 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 (Daniel, Grinblatt, Titman, and Wermers, 1997) 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% level 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	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	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	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 IA2. Round-trip Returns and Monthly Based Returns

In this table, we present the equal-weighted round-trip returns earned by industry 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 five-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 IA3. Holdings-Based Calendar-Time Portfolios

This table presents robustness tests for Table 3, Panel B under different specifications. Panel A replicates the analysis excluding the year 1991 from the time series of portfolio returns. In Panel B, 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 (). In Panel C, each observation in the regression, i.e., each day in the time series of portfolio returns, is weighted 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 (Daniel, Grinblatt, Titman, and Wermers, 1997) size quintile.

Panel A: Excluding 1991

	All Retail Traders	All Insider Trades	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 Insider Trades	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 IA3. Holdings-Based Calendar-Time Portfolios (Cont.)

Panel C: Days Weighted by Number of Stocks in Portfolio

	All Retail Traders	All Insider Trades	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 Insider Trades	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 IA4. Transactions-Based Calendar-Time Portfolios

This table presents robustness tests for Table 4 under different specifications. Panel A repeats the analysis of Table, where portfolios are equally-weighted within days. Panels B and C report figures computed analogously to Table 4 and Table IA4, Panel A, respectively, 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. Panels D and E replicate the analysis presented in Table 4, and Table IA4, Panel A, respectively, excluding microcap stocks, defined as stocks in the lowest DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997) size quintile. Panels F and G replicate the analysis presented in Table 4, and Table IA4, Panel A, respectively, using a six-month holding period. Panels H and I replicate the analysis presented in Table 4, and Table IA4, Panel A, respectively, using a three-month holding period.

Panel A: Equal-Weighted Portfolios, Days Weighted by Number of Trades

	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

Panel B: 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 C: 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

Table IA4. Transactions-Based Calendar-Time Portfolios (Cont.)

Panel D: 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

Panel E: 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 F: 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 G: 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 IA4. Transactions-Based Calendar-Time Portfolios (Cont.)

Panel H: 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 I: 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 IA5. Buy-and-Hold Abnormal Returns, 12 Months

This table shows results analogous to those reported in Table IA1, 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, and 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 returns (Daniel, Grinblatt, Titman, and Wermers, 1997) 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% level 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	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	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	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 IA6. 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 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. A stock purchase or sale by a corporate insider is classified as Local if the headquarters of the traded firm is within 250 miles of the headquarters of the insider's firm(s). In Panel A (Panel B), we report equal-weighted (trade size–weighted) three-month buy-and-hold DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997). 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% level 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 IA7. Expertise Trades in Hard-to-Value Stocks, 12-Month DGTW-Adjusted Returns

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, and 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 (Daniel, Grinblatt, Titman, and Wermers, 1997) 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% level 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							
Small	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)
Big	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)
Small - Big	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 IA7. 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 IA8. Trading Frequency and Expertise Trades

This table presents a robustness test for the results presented in Panel E of Table A1. Column 1 to 3 present results obtained using all the corporate insiders in the sample. Columns 4-6 present results obtained after excluding the top 10% of insiders ranked by number of expertise trades. We repeat the test for the eight industry definitions considered in Appendix D, but report results for only three of them in order to save space. Stock returns are winsorized at the 1% level. *t*-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated with ***, **, and *, respectively.

Equal-Weighted DGTW-Adjusted 3-Month Buy-And-Hold Abnormal Returns						
	All Insiders			Excluding Top 10% of Insiders by Number of Expertise Trades		
Expertise Definition	3 Digit SIC	2 Digit SIC	12FF	3 Digit SIC	2 Digit SIC	12FF
	(1)	(2)	(3)	(4)	(5)	(6)
Purchases (n)	214	333	688	109	173	377
Sales (n)	199	317	589	101	199	337
Buy	2.76*	2.44**	1.49*	6.46***	4.95***	2.02*
	(1.66)	(1.99)	(1.83)	(2.67)	(2.74)	(1.73)
Sell	-3.11*	-2.03*	-0.543	-4.84**	-1.783	-0.504
	(-1.90)	(-1.69)	(-0.57)	(-2.18)	(-1.21)	(-0.40)
Buy-Sell	5.87**	4.47***	2.033	11.30***	6.74***	2.521
	(2.52)	(2.60)	(1.62)	(3.44)	(2.89)	(1.47)

Table IA9. 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, and 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. Twenty-three out of 105 industry 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 (12-month) equal-weighted DGTW-adjusted excess returns (Daniel, Grinblatt, Titman, and Wermers, 1997) are reported in Panel A (Panel B). 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% level is indicated with ***, **, and *, respectively.

Panel A: Three-Month DGTW-Adjusted Returns

	All Insiders	Financial Firm Insiders	Non-Financial Firm 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 IA9. Financial Firm Insiders (Cont.)

Panel B: 12-Month DGTW-Adjusted Returns

	All Insiders	Financial Firm Insiders	Non-Financial Firm 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)

Figure IA1. Do Insiders Trade More Before the Traded Firm Earnings Announcements?

Figure IA1a shows the average daily percentage of buy trades for expertise and non-expertise trades of insiders around the traded-firm's earnings announcements, as well the fraction of trades by other traders in the retail trading database. Trades are shown for intervals of five trading days around the traded firm's earnings announcement. Analogously, Figure IA1b presents the share of sell trades around the traded-firm's earnings announcements.

Figure IA1a. Distribution of Buy Trades Relative to the Traded Firm's Earnings Announcements

Figure IA1b. Distribution of Sell Trades Relative to the Traded Firm's Earnings Announcements

Figure IA2. Do Insiders Trade More Before Own-Firm Earnings Announcements?

Figure IA2a shows the average daily percentage of buy trades for expertise and non-expertise trades of insiders around their own-firm earnings announcements. Trades are shown for intervals of five trading days around the own-firm earnings announcement. Analogously, Figure IA2b presents the share of sell trades around own-firm earnings announcements.

Figure IA2a. Distribution of Buy Trades Relative to Own-Firm Earnings Announcements

Figure IA2b. Distribution of Sell Trades Relative to Own-Firm Earnings Announcements